



NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

**WHAT ARE WE WAITING FOR? CUSTOMER WAIT
TIME, FILL-RATE, AND MARINE CORPS EQUIPMENT
OPERATIONAL AVAILABILITY**

by

Jason H. Fincher

December 2016

Thesis Advisor:
Co-Advisor:

Kenneth Doerr
Chad Seagren

Approved for public release. Distribution is unlimited.

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE			<i>Form Approved OMB No. 0704-0188</i>	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC 20503.				
1. AGENCY USE ONLY (Leave blank)		2. REPORT DATE December 2016		3. REPORT TYPE AND DATES COVERED Master's thesis
4. TITLE AND SUBTITLE WHAT ARE WE WAITING FOR? CUSTOMER WAIT TIME, FILL-RATE, AND MARINE CORPS EQUIPMENT OPERATIONAL AVAILABILITY			5. FUNDING NUMBERS	
6. AUTHOR(S) Jason H. Fincher				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			10. SPONSORING / MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB number ____N/A____.				
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.			12b. DISTRIBUTION CODE	
13. ABSTRACT (maximum 200 words) This research explores the effects of customer wait time (CWT) and fill-rate on equipment operational availability (A_o) using consumable repair parts requisition data from Marine Corps mechanized units to determine 1) the relationship between CWT, fill-rate, and A_o ; and 2) if the system's reliance on fill-rate as the primary indicator of supply chain performance adversely affects A_o . This study also captures observations on the quality and scope of Ground Combat Support System—Marine Corps (GCSS-MC) data. Analysis methods include linear regression techniques and a categorization model developed specifically to compare supply chain outcomes reported by CWT versus those reported by fill-rate. This study concludes that both fill-rate and CWT are important measures, but neither is sufficient as a single indicator of supply chain performance. The reliance on fill-rate alone currently results in misreporting of supply chain outcomes between 20–40% of the time. These findings support policies that balance inventory performance with supply chain responsiveness, focusing efforts on items with long CWTs. The data also suggests logical CWT standards that differ from current policy. The scope and quality of the GCSS-MC data indicate that data collection processes could be further automated and focused on the drivers of days-dead-lined.				
14. SUBJECT TERMS Fill-rate, customer wait time, operational availability, days dead-lined, Ground Combat Support System—Marine Corps, consumable repair parts			15. NUMBER OF PAGES 75	
			16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT UU	

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release. Distribution is unlimited.

**WHAT ARE WE WAITING FOR? CUSTOMER WAIT TIME, FILL-RATE, AND
MARINE CORPS EQUIPMENT OPERATIONAL AVAILABILITY**

Jason H. Fincher
Major, United States Marine Corps
B.S., University of Southern California, 2005
M.S., Syracuse University, 2013

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN MANAGEMENT

from the

**NAVAL POSTGRADUATE SCHOOL
December 2016**

Approved by: Kenneth Doerr, Ph.D.
Thesis Advisor

Chad Seagren, Ph.D.
Co-Advisor

Chad Seagren, Ph.D.
Academic Associate
Graduate School of Business and Public Policy

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

This research explores the effects of customer wait time (CWT) and fill-rate on equipment operational availability (A_O) using consumable repair parts requisition data from Marine Corps mechanized units to determine 1) the relationship between CWT, fill-rate, and A_O ; and 2) if the system's reliance on fill-rate as the primary indicator of supply chain performance adversely affects A_O . This study also captures observations on the quality and scope of Ground Combat Support System—Marine Corps (GCSS-MC) data. Analysis methods include linear regression techniques and a categorization model developed specifically to compare supply chain outcomes reported by CWT versus those reported by fill-rate. This study concludes that both fill-rate and CWT are important measures, but neither is sufficient as a single indicator of supply chain performance. The reliance on fill-rate alone currently results in misreporting of supply chain outcomes between 20–40% of the time. These findings support policies that balance inventory performance with supply chain responsiveness, focusing efforts on items with long CWTs. The data also suggests logical CWT standards that differ from current policy. The scope and quality of the GCSS-MC data indicate that data collection processes could be further automated and focused on the drivers of days-dead-lined.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

I.	INTRODUCTION.....	1
A.	OVERVIEW.....	1
B.	PURPOSE.....	2
C.	RESEARCH QUESTIONS.....	2
D.	SCOPE AND METHODOLOGY	3
1.	Scope.....	3
2.	Methodology	3
E.	EXPECTED BENEFITS OF THE STUDY	4
F.	ORGANIZATION OF THIS REPORT.....	4
II.	BACKGROUND AND LITERATURE REVIEW	5
A.	EQUIPMENT READINESS AND OPERATIONAL AVAILABILITY.....	5
B.	CUSTOMER WAIT TIME.....	7
C.	FILL-RATE.....	10
D.	SUMMARY	14
III.	METHODOLOGY	15
A.	DATA SOURCES AND COMPILATION	15
1.	Data Tables.....	16
2.	Important Data Fields	17
3.	Derived Fields and Dummy Variables	18
B.	ANALYSIS METHODS.....	20
1.	Linear Regression Analysis.....	20
2.	Categorization and the Comparison Framework	21
C.	ASSUMPTIONS AND LIMITATIONS IN THE DATA	24
1.	Assumptions in the Data.....	24
2.	Limitations of the Data	25
D.	CHARACTERISTICS OF DATA USED IN ANALYSIS	25
IV.	ANALYSIS AND RESULTS	29
A.	LINEAR REGRESSION RESULTS	29
B.	RESULTS OF DATA CATEGORIZATION.....	32
1.	Sensitivity Analysis of the Categorization Model	35
2.	Sensitivity to the CWT threshold	37
C.	GCSS-MC DATA QUALITY	40
D.	EFFECT ANALYSIS.....	41

V.	SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS	43
A.	EFFECTS OF CWT AND FILL RATE ON EQUIPMENT READINESS.....	43
1.	Summary and Conclusions.....	43
2.	Recommendations	44
B.	FILL-RATE AS THE SINGLE SUPPLY CHAIN METRIC.....	45
1.	Summary and Conclusions.....	45
2.	Recommendations	45
C.	GCSS-MC DATA QUALITY	46
1.	Summary and Conclusions.....	47
2.	Recommendations	47
D.	LIMITATIONS OF THE MODEL	48
E.	RECOMMENDATIONS FOR FURTHER RESEARCH	49
	APPENDIX. DATA TABLES AND FIELDS.....	51
	LIST OF REFERENCES	53
	INITIAL DISTRIBUTION LIST	57

LIST OF FIGURES

Figure 1.	Uptime and Downtime Distribution. Adapted from Pryor (2008).....	6
Figure 2.	Characteristics of Fill-Rate versus Customer Wait Time.	22
Figure 3.	Distribution and Summary Statistics of Variables.....	26
Figure 4.	Interaction Profiles.....	31
Figure 5.	Sensitivity to Fill-Rate	36
Figure 6.	Sensitivity Analysis to CWT	38
Figure 7.	CWT versus Fill-Rate Reported Outcomes	39

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF TABLES

Table 1.	Linear Regression Summary.....	30
Table 2.	Categorization Results.	33
Table 3.	Categorization Results with Fill-Rate of 50%	37
Table 4.	Effects Report	42

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

Ao	Operational Availability
AAC	Acquisition Activity Code
AAV	Amphibious Assault Vehicle
ALDT	Administrative and Logistics Delay Time
CONUS	Continental United States
CWT	Customer Wait Time
DASF	Due in Status File
DDL	Days Dead-lined
DOD	Department of Defense
DRRS-MC	Defense Readiness Reporting System—Marine Corps
ERO	Equipment Repair Order
GCSS-MC	Global Combat Support System—Marine Corps
IG	Inspector General
LAV	Light Armored Vehicle
MAGTF	Marine Air Ground Task Force
MEE	Mission Essential Equipment
MTRR	Maintenance Time/ Time to Repair
MRR	Maintenance Readiness Reporting
NSN	National Stock Number
RIP	Repairables Issue Point
SCM	Supply Chain Management
SECREP	Secondary Repairable Item
SKU	Stock Keeping Unit
SMU	Supply Management Unit
UMMIP	Uniform Material Movement and Issue Priority
UND	Urgency of Need Designator
USD(AT&L)	Under Secretary of Defense for Acquisitions, Technology, & Logistics

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my thesis advisors, Dr. Kenneth Doerr and Dr. Chad Seagren, for their assistance and mentorship. Their interest and enthusiasm in the topic made this a truly enjoyable experience. I also wish to express my appreciation to Huntley Bodden from Marine Corps Logistics Command for taking an interest in this topic and providing GCSS-MC data and support. Finally, I would like to thank my family for their patience, understanding, support, and encouragement throughout this process.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

A. OVERVIEW

As one of the three pillars of the Department of Defense's (DOD) Title 10 mission to *man, train, and equip* the force, equipment operational availability (A_O) is of paramount importance to the Marine Corps and DOD. This research focuses on specific areas of the Marine Corp maintenance cycle that involve actions taken in pursuit of operational readiness by both the supply and maintenance functional areas of the Marine Corps logistics community. Supply chain management within DOD is a complementary field of study that influences Marine Corps practices and capabilities in this area.

Since 2000, a number of Department of Defense initiatives have directed the use of Customer Wait Time (CWT) as a measure of supply chain performance (Department of Defense [DOD], 2000). CWT is defined as “the total time elapsed between issuance of a customer order and satisfaction of the order” (United States Marine Corps [USMC], 2014, pp. 2–29). In theory, managing CWT can lead to increased supply chain performance and reduced costs through reductions in inventories (Dumond et al., 2001).

The Marine Corps has been reluctant to embrace CWT as a key performance indicator and instead relies on the metric of “fill rate,” which is commonly known as the ratio of demanded items filled from a local inventory to the total number of items demanded over a particular period (Fricker & Robbins, 2000). Fill-rate is a widely used metric for setting inventory levels and is also a useful measure of customer satisfaction. In general, high fill-rates can be achieved at the expense of maintaining large inventories. Unfortunately, Marine Corps units must often operate in inventory constrained environments such as aboard naval shipping or during other expeditionary operations. Fiscal constraints also continuously limit inventory purchases that affect fill-rate. An alternate method for maintaining acceptable fill-rates is through managing CWT to the source of supply. In theory, acceptable fill-rates can be achieved with smaller inventories for items with fast delivery times. The primary shortfall of using fill-rate, is that the metric does not account for the length of time required to receive a back-ordered item.

Currently, if a part is out-of-stock at the local source of supply, requesting units shift their effort to expediting delivery times. This practice represents *reactive* CWT management. *Proactive* CWT management in the form of actively maintaining a tracking CWT for all parts, even those that are normally in stock, may provide better overall responsiveness and could identify parts that do not need to be stocked to high levels because their CWT is acceptably short. In the current system, a part that normally experiences a high fill-rate may possess an unacceptably long CWT when it unexpectedly stocks out. Current Marine Corps inventory management practices do not necessarily recognize or account for this problem.

New technology offers an opportunity to further explore this issue. In 2012, the Marine Corps completed the initial fielding of an Oracle based Enterprise Resource Planning (ERP) system called Global Combat Support System–Marine Corps (GCSS-MC). The capabilities of this system provide new opportunities for data collection and analysis, including more accurate tracking of CWT and fill-rates. GCSS-MC provides Marine Corps Logistics Command (LOGCOM) increased visibility on inventory and supply activity levels. LOGCOM is currently considering centralizing the management of consumable parts and is actively exploring options for effective performance metrics.

B. PURPOSE

The purpose of this research is to not only explore the effect of CWT and fill-rate on equipment operational availability using GCSS-MC data, but also to determine if the current system's reliance on fill-rate as the primary indicator of supply chain performance adversely affects equipment A_0 .

C. RESEARCH QUESTIONS

This study examines two primary research questions. Given that this study deals with a relatively new data source, a third, secondary research question is also considered:

1. To what extent does CWT and fill-rate for consumable repair parts affect the equipment readiness of Marine Corps mechanized systems?
2. Does reliance on fill-rate as the exclusive indicator of supply chain performance have negative impact on supply-chain performance?

3. Are current data collection practices that use GCSS-MC sufficient to provide Marine Corps supply-chain managers the information they need for accurate and timely decision making?

D. SCOPE AND METHODOLOGY

1. Scope

The scope of this research is limited to the examination of Marine Corps consumable repair parts for mechanized units reaching back approximately three years when GCSS-MC began capturing data.

In order to reduce the size of the data set to manageable proportions, analysis is intentionally limited to parts requisitions from mechanized units consisting of Tanks, Light Armored Vehicles (LAV), and Amphibious Assault Vehicles (AAV). Also, due in part to their high profile within the Marine Air Ground Task Force (MAGTF) these types of units tend to have a culture of maintenance that may serve to reduce error in time-stamp data for supply requisitions attributable to varying supply processes observed in units without this same culture.

Secondary repairable parts (SECREPS) are excluded from the analysis because the supply chain procedure for SECREPS differs widely from that of consumable repair parts and they must be considered separately.

Concepts and analysis developed in this thesis have wider applications among other Marine Corps equipment groups, but due to unique processes within the Marine Corps supply chain, some conclusions may not directly apply to other DOD services or outside agencies.

2. Methodology

This research utilizes regression techniques on data collected by GCSS-MC to examine the statistical relationships between factors affecting A_0 . Since A_0 contains many aspects that are not captured in the data set, the surrogate variable of Days-Dead-Lined (DDL) is used as the dependent variable. DDL and A_0 have an inverse relationship that is explained further in Chapter III, Methodology. CWT and monthly fill-rate per order are the independent variables considered. Each value is the result of transformations performed on GCSS-MC data for requisitions placed by the

abovementioned units. Data transformations required to get to the metrics used for analysis are also explained further in Chapter III.

Once the relationship between CWT, fill-rate and DDL is identified, this study further explores the nature of the relationship by establishing thresholds for acceptable and unacceptable levels for each metric and then categorizing the data into a quad-chart of acceptable and unacceptable outcomes. The resulting framework provides insight into supply chain performance that is not apparent using the linear regression model and provides quantifiable information on areas that fill-rate may be misreporting performance.

E. EXPECTED BENEFITS OF THE STUDY

Examining how CWT and fill-rate interact in the context of current Marine Corps supply chain practices and their impact on equipment availability can be used to enable long-term supply chain process improvement. A better understanding of the effects of the selected metrics could also result in more efficient Marine Corps materiel readiness resource allocations.

GCSS-MC is an operational database, used for daily performance of work tasks. At this time analysis of GCSS-MC data is largely absent from literature. Data transformation methods utilized in this study, such as the use of DDL as a surrogate for AO, can be adapted or duplicated for further analysis of other supply chain issues. GCSS-MC is still evolving and is a relatively immature ERP system. Observations on the current quality and completeness of the data set can be used to adjust work processes that improve data collection so that future studies have more accurate and complete data for analysis.

F. ORGANIZATION OF THIS REPORT

The following chapter further discusses the background of this issue within the DOD and the Marine Corps. Chapter II also highlights current practices and selected related research in supply chain management. Chapter III includes the methodology for analysis including information about the data set, necessary data transformations, and the theoretical framework for analysis. Chapter IV presents the results of the analysis. A summary of findings, conclusions, and recommendations are discussed in Chapter V.

II. BACKGROUND AND LITERATURE REVIEW

The field of supply chain management (SCM) is rich with studies of performance metrics and forecasting models. The discipline is maturing, though there are indications that not much empirical work has changed since 2007 (Piotrowicz & Cuthbertson, 2015). Several studies have attempted to equate CWT with A_O for the Department of Defense (DOD). A 2007 Inspector General's report found that DOD could not link CWT to A_O (Inspector General [IG], 2007). A Naval Postgraduate School MBA project by Thorn and Hubbard (2007), used simulations to model a monetary relationship between CWT and A_O for Marine Corps amphibious assault vehicles using data from legacy supply support systems focusing on the effects demand variation. Thorn and Hubbard's model implied that improvements to A_O were possible by reducing CWT at various service levels, but results were limited by the quality of the data and the simplification steps required to run a simulation.

This study attempts to answer the question by exploring three potential indicators of supply chain performance: equipment readiness, customer wait time, and fill-rate. This chapter will explore each of the variables of concern by providing definitions and historical context of the measures within DOD and the Marine Corps. It will also provide some current management insights from industry and academia concerning each measure and its use outside of the DOD.

A. EQUIPMENT READINESS AND OPERATIONAL AVAILABILITY

Equipment readiness and operational availability (A_O) are closely related. The terms are often used interchangeably, though that is not technically correct. Readiness, sometimes called the "R" rating (USMC, 2012b), is considered a primary measure of a unit's combat readiness. The "R" rating is the most-often-briefed and highest profile metric that relies on the supply and maintenance systems. The Marine Corps Integrated Maintenance Management System (MIMMS) Field Manual (2012d) defines equipment readiness as "the portion of the unit's equipment readiness or ability to perform its mission as determined by the condition of the equipment resources allocated to the unit"

(pp. 1–6). Stated differently in the Marine Corps’ Ground Equipment Condition and Supply Readiness Reporting (MRR) policy (2012b) the “R” rating is the total number of items possessed less those that are dead-lined¹ divided by the total number of items possessed.

$$\text{Readiness (R)} = \frac{\text{Possessed} - \text{Dead-lined}}{\text{Possessed}}$$

“R” rating provides a percentage of total assets available at a particular snapshot in time, whereas Ao provides the percentage of time a single item is available (Thorn & Hubbard, 2007). A_O is generally defined as the amount of time a piece of equipment is “up” versus the total time examined (Pryor, 2008).

$$A_o = \frac{\text{Uptime}}{\text{Total time}} \quad \text{or} \quad \frac{\text{Uptime}}{\text{Uptime} + \text{Downtime}}$$

Downtime is composed of maintenance time/time to repair (MTTR) and administrative and logistics delay time (ALDT). Historically, total ALDT is the largest contributing factor for downtime (Pryor, 2008). CWT is a contributing factor to ALDT as shown in Figure 1.

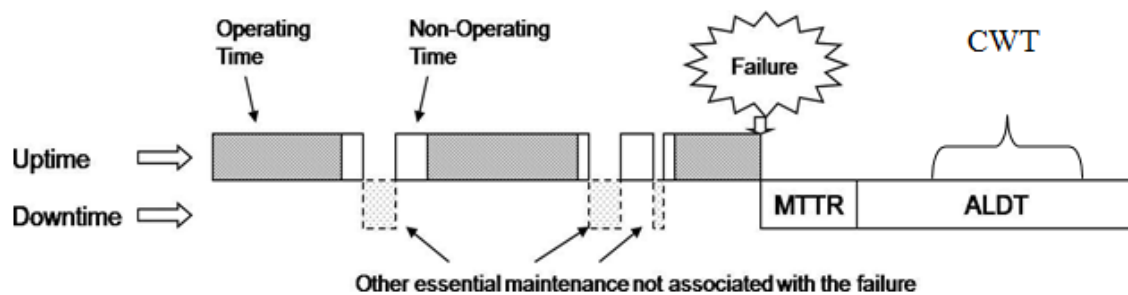


Figure 1. Uptime and Downtime Distribution. Adapted from Pryor (2008).

¹ The Marine Corps uses the term “dead-lined” to indicate equipment that is not operationally available due to a maintenance issue. The term comes from the practice of lining up equipment while awaiting parts on the “dead” line.

“R” rating is the metric of concern for commanders. They are responsible for reporting their unit’s “R” rating monthly via the Defense Readiness Reporting System-Marine Corps (DRRS-MC) (USMC, 2012b). DRRS-MC operates on the Marine Corps’ classified Internet and does not communicate with the unclassified networks that are used by supply and maintenance. Readiness levels are entered by hand into DRRS-MC and there is not a system of verification that checks DRRS-MC against GCSS-MC. The information integrity issues with this process and classification differences between the systems make it challenging to compare recorded “R” ratings to the A_O calculated via other supply and maintenance systems. Theoretically, the average “R” rating for a set of equipment over time should be roughly equivalent to the aggregated A_O for that same equipment set over the same period of time.

Acknowledging the subtle differences in the measures, this study will focus on A_O because: 1) we can assume that an improvement in overall A_O reduces equipment downtime that in turn should increase the average “R” rating over time, 2) the information can be approximated using unclassified data in GCSS-MC, and 3) A_O is defined in terms of time as is another variable of concern: CWT.

B. CUSTOMER WAIT TIME

In 1995 the U.S. Army implemented a logistics program called the Velocity Management (VM) initiative to improve speed and accuracy of their logistics pipeline (Dumond et al., 2001). This methodology introduced the time-based metric of Customer Wait Time (CWT) to the DOD as the time between order and that order’s fulfillment (Dumond et al., 2001). In the VM context, CWT is considered the primary indicator of logistics performance and drives process improvement efforts (Dumond et al., 2001). “Order-to-delivery time,” and “total order cycle time” are common synonyms for the DOD’s definition of CWT used in industry and academia (Gunasekaran, Patel, & Tirtiroglu, 2001).

In December of 2000, due in part to the success of VM, the Under Secretary of Defense for Acquisitions, Technology and Logistics (USD [AT&L]) directed all services to establish a CWT metric in order to measure supply chain performance (DOD, 2000).

Starting in 2002, CWT information was collected and reported by Marine Corps Logistics Command (LOGCOM). Reported CWTs were substantially higher than established goals through 2005. The Marine Corps consistently reported the highest CWT of any of the services, though reported times were skewed by including customers above the organizational level, which was not the intent of the reporting requirement (IG, 2007).

In September 2010, the Commandant of the Marine Corps re-published guidance that identified *time definite delivery* standards as a part of the uniform material movement and issue priority system (UMMIPS). This guidance directed the Deputy Commandant for Installations and Logistics to “develop internal performance goals for measuring performance against the UMMIPS time standards” (USMC, 2010 p. 3). There was no mention of CWT as a specific metric in this guidance. The 2014 DOD Manual for supply chain metrics elevated CWT as the central metric by which to gauge “reliability and effectiveness of logistics processes.” (DOD, 2014 p. 6). Also in 2014, the Marine Corps’ republished consumer level supply manual included a definition of customer wait time as the “total time elapsed between issuance of a customer order and satisfaction of the order” and designated it as a required element of a “demand-supported stock level” (USMC, 2014 p. 2–29). There was no further guidance on how to incorporate or use CWT provided in this guidance.

There is a growing recognition in SCM literature for the importance of time sensitivity. Lean Logistics popular in the mid-1990s tempted supply chain managers to reduce inventory levels to minimal levels by matching inventory levels with demand quantities in order to realize cost savings through the elimination of waste (Jones, Hines & Rich, 1997). Improvements to CWT through faster and more expensive methods of transport can often justify their expense due to corresponding reduction in the requirement for on-hand inventory (Gunasekaran, Patel, & Tirtiroglu, 2001) but a strict lean approach is only appropriate when demand is predictable, product variety is low, and volume of demand is high (Christopher, 2000). These are not common characteristics for Marine Corps repair parts.

One of the primary criticisms of the lean approach is its inability to deal with demand variability that has led to the development of a concept termed “agile supply

chain” solutions (Hines, Howle, & Rich, 2004). In contrast to lean, the key characteristic of an agile supply chain is the ability to adapt to changing conditions, or flexibility (Christopher, 2000). Agile logistics is appropriate for situations where “demand is less predictable, and volume at the individual stock keeping unit (SKU) is low” (Christopher, 2000, p 37). An organization will have some products that fit well with lean approaches, and others that require agility (Christopher 2007). Agile logistics key characteristic is responsiveness. In industry, CWT is a widely used measure of responsiveness. Christopher (2000) observed the following:

The importance of time as a competitive weapon has been recognized for some time (Stalk, 1988). The ability to be able to meet the demands of customers for ever-shorter delivery times, and to ensure that supply can be synchronized to meet the peaks and troughs of demand, is clearly important in this era of time-based competition. (Stalk & Hood, 1990, p. 37)

Within DOD there is growing support for a shift from large conventional support structures to more focused “sense and respond” models (Griffin, 2002). With the quickly changing requirements of today’s smaller-scaled conflicts, Marine Corps supply operations require agility. Concurrently, budgetary constraints are applying pressure to look for cost saving measures such as reducing inventory levels. Inventory managers should understand that leaning the supply system comes with risk. That risk can be mitigated in part by improving CWT and making the supply system more agile.

Methods to improve CWT vary with the situation and design of the organizations supply chain. Martin and Patterson’s (2009) research indicates that inventory and cycle time performance metrics should be used in concert to best position an organization in a supply chain network. Thorn and Hubbard (2007) explored the effects of pre-positioning inventory to reduce CWT for expeditionary operations. While potentially effective, their method relied on accurate inventory forecasting that as you will read next, is problematic for the Marine Corps.

C. FILL-RATE

The Marine Corps has been reluctant to embrace CWT as a key performance indicator in the supply chain. Per 2015 Government Accountability Office (GAO) Report, “the Marine Corps has not established a service wide customer wait time standard” (GAO, 2015). The Marine Corps supply community continues to rely instead on the metric of “fill-rate” as a measure of performance at the intermediate level. Though an official definition of the term is absent from recent Marine Corps directives and publications, the term is often referenced in Marine Corps correspondence and guidance (USMC, 2012c and Berg, 2013). Fill-rate is commonly known within DOD to mean the ratio of demanded items filled out of a local inventory to the total number of items demanded over a particular period (Fricker & Robbins, 2000). Use of this formula assumes that the period covered is sufficient to capture an entire order cycle.

$$\text{Fill-rate} = \frac{\text{Items filled from stock}}{\text{Items demanded}}$$

The metric is used conventionally to calculate safety stock levels and as a measure of customer satisfaction. The term “fill-rate” is relatively common in the Defense Acquisitions field for calculating initial acquisition quantities of systems and spares. The definition of the term, as used in acquisitions, appears to have evolved somewhat, incorporating a time component. The Defense Contract Management Agency defines the fill-rate in their Performance Based Logistics (PBL) Support Guidebook, but adds a time element by defining the term as “the volume of requisitions satisfied within the initial response time” (Defense Contract Management Agency, 2002 p. 8).

Fill-rate is commonly used in industry and is closely associated and often confused with the term service level that is more common in management literature. *Service Level* is the probability of not running short of stock during the replenishment time, which is mathematically identical to the ratio of order cycles that a firm stocks-out over the total number of order cycles (Coleman, 2000). This ratio is the *percentage of time* that a firm does not run short of stock. Service level is sometimes referred to as *type*

1 service level (Nahmias, 2009) or *cycle service level* (Coleman, 2000). A shortcoming of service level is that it does not account for the number of items a firm will be short during a stock-out and as a consequence can overstate inventory performance or customer satisfaction (Coleman 2000). Fill-rate, sometimes called *type 2 service level* (Nahmias, 2009) or *annual service level* (Coleman, 2000) does account for the number of items stocked out and is commonly used by practitioners in the field, though it is often confused with the cycle service level (Coleman, 2000). Fill-rate is the *percentage of orders* met from stock. Though fill-rate and service level are not synonymous, it is relatively simple to convert fill-rate to service level and vice versa (Nahmias, 2009). Both terms are used separately to calculate required safety stock inventory levels in order to meet expected customer demand (Coleman, 2000).

There are two types of organizations within the Marine Corps that report performance in terms of fill-rate: Repairables Issue Points (RIP), and Supply Management Units (SMU). Each major Marine Corps installation has one RIP and one SMU that provide services to the units assigned to that installation. Smaller, temporary RIPs and SMUs may be established for other operations or exercises. Fill-rate can provide a valuable measure of customer satisfaction for either organization but it can be argued that the measure is less useful as a gauge of performance for the SMU than for the RIP.

Secondary repairable items (SECREP), also known as spares are managed by an RIP. SECREPs are typically critical repair assemblies that require consistently high fill-rates to satisfy maintenance customers. SECREPs also have a high enough acquisition cost to justify the expense of repairing them vice replacing them in the supply system. The initial acquisition process for SECREPs uses fill-rates conventionally to forecast required repairable inventory levels at the time of system acquisition. Fill-rate used as a performance metric for customer satisfaction is largely a consequence of assumptions made during forecasting including anticipated failure rates. SECREPs, once acquired, stay in a relatively closed system. Upon failure, a SECREP returns to the RIP for repair and eventual reissue. This makes fill-rate easier to manage and maintain because a single purchase elevates the average fill-rate unless the SECREP is no longer repairable or exits

the system for some other reason. In the case of the RIP, fill-rate provides a management tool that indicates when additional acquisitions of spares may be required.

Consumable repair part stock levels are managed separately by the SMUs. An SMU acts as both the warehouse and issue point for requesting customers. Consumable parts are disposed of by the user when they fail. As such, the SMU does not enjoy the same closed system as the RIP and does not have the ability to affect long-term fill-rates with a single purchase. Inventory managers are given some flexibility in determining stock levels so long as it is based on actual demand history. They are directed to consider operating level, lead-time, and defined safety levels to manage stock levels to minimize total variable costs (USMC, 2012a). In practice, SMUs typically employ variations of a simple moving average forecast, adjusted according to observation and experience to determine stock levels. This relatively simple forecasting method may not be adequate to achieve exceptionally high fill-rates

A primary method to improve fill-rate for an individual part without incurring a significant inventory cost is to improve the accuracy of the demand forecast and then stock accordingly. Service parts experience intermittent demand characterized by periods of zero demand, randomly mingled with periods of inconsistent demand quantity (Willemain, Smart, & Schwarz, 2004). This makes forecasting demand for repair parts particularly difficult (Willemain et al., 2004), but scholars have proposed a number of methods that improve intermittent demand forecasting over simple methods (Willemain et al., 2004, and Syntetos & Boylan, 2006).

There are well known methods for forecasting intermittent demand. The “Croston Method,” developed in 1972, relies on exponential smoothing and is widely used in fields that experience intermittent demand (Shenstone & Hyndman, 2005). Shenstone and Hyndman (2005) explore the Croston method’s underlying assumptions and provide modifications to adapt the model to better meet the characteristics of intermittent demand.

Simplistic inventory stocking policies is one of the fourteen common SCM pitfalls identified by Lee and Billington (1992). During their study of automobile supply

parts warehousing, they found that the organization could reduce inventory investment by as much as 40% while maintaining the same customer service level by adjusting stocking policies to account for uncertainty. (Lee & Billington, 1992).

While fill-rate can be a very useful tool, it also has some well documented shortcomings. Fill-rate tends to measure performance strictly from the supply system's perspective and does not fully capture the satisfaction level of the maintenance customers (Fricker & Robbins 2000). Supply chain metrics that measure each site autonomously is the number one common SCM pitfall identified by Lee and Billington (1992) and results in inefficiencies for the overall chain and an "inadequate definition of customer service" is the number two pitfall. While fill-rate does capture the number of parts on back-order, it does not account for the length of time a part is in a back-order status so it cannot be directly related to A_O .

Because fill-rate is measured one part at a time, the chances of a stock-out that impacts a repair increases with the number of parts required for that repair. A fill-rate of less than 100% for each required part contributes to an increasing cumulative probability that not all of the parts will be in stock. (Fricker & Robbins, 2000). For example, a repair that requires five parts at a 70% fill-rate will have a $(0.7 \times 0.7 \times 0.7 \times 0.7 \times 0.7)$ or 16.8% chance of getting filled completely from stock on the first pass. Fricker and Robbins (2000) referred to this as *equipment repair order (ERO) fill-rate*; current vernacular for this measure is the *service request fill-rate*.

Since fill-rate is not penalized for over-stocking, it can be improved by carrying large inventories. Researchers at RAND developed a method called Dollar Cost Banding that encourages stocking only higher demand, low cost critical items and those higher cost critical items with known long lead times in order to maximize average fill-rate with minimum investment while addressing operational concerns by stocking long lead time critical parts (Fricker & Robbins, 2000). This method only addresses the average fill-rate and it leaves open the possibility for individual parts with unknown long lead times to impact operational readiness. It also does not fully address the service request fill-rate nor does it address differences in the criticality of the parts.

D. SUMMARY

DOD and Marine Corps supply chain policies are maturing, but practical application is lagging behind. There is growing evidence that DOD and the Marine Corps require more agile solutions to both improve responsiveness and reduce costs with the overall goal of maintaining acceptable A_0 . Agile logistics solutions focus on responsiveness and show potential to meet the operational goals under budgetary constraints. CWT is a measure of responsiveness, but it is most effective when it is not divorced from inventory decisions.

Fill-rate is a valuable tool for calculating safety stock and measuring customer satisfaction, but the applicability of fill-rate is not well understood within the Marine Corps logistics community. Relatively successful results using fill-rate to report inventory performance for SECREPs have contributed to an over-confidence in fill-rate as a single measure of supply chain performance. In many cases fill-rate is used unconventionally for purposes that the metric is not well suited. Specifically, the simple methods used for forecasting intermittent demand of consumable repair parts imposes a relatively low upper bound for fill-rate levels.

This study aims to clarify some of these misconceptions and provide feasible recommendations to improve Marine Corps supply chain practice.

III. METHODOLOGY

The first goal of this study is to establish the relationship between CWT, Fill-rate and DDL by fitting the data to a linear regression model. The first section of this chapter outlines the data sources and steps taken to refine the data used for analysis.

This next goal of this study is to demonstrate the impact of the current fill-rate-only metric system against one that uses both fill-rate and CWT. This is accomplished by establishing thresholds for acceptable and unacceptable levels for each metric and then categorizing the data into acceptable and unacceptable outcomes. The results reveal areas where fill-rate is potentially misreporting performance and areas where short customer wait times could potentially suffice for inventory management.

A. DATA SOURCES AND COMPILATION

The data consists of maintenance and supply transaction information for three families of vehicles: Tanks, Amphibious Assault Vehicles (AAVs) and Light Armored Vehicles (LAVs). The raw data covers a three-year range from 2012 to 2015. It includes 27,714 distinct service requests and 13,446 unique NSNs ordered via 247,967 document numbers.

Marine Corp Logistics Command (LOGCOM) provided data collected by GCSS-MC as Microsoft Excel Comma Separated Values (CSV) files. Upon request, LOGCOM also provided the number of days dead-lined for each service request and a list of all authorized Acquisition Advice Codes (AAC) associated with Repairable Issue Points (RIPs).

Data cleaning and coding was accomplished using a combination of Microsoft Access to reestablish relationships between tables and query the results, and Microsoft Excel to perform data transformations (Microsoft Office 2013 64-bit edition). Statistical analysis was performed using JMP® Pro 12 software.

1. Data Tables

The raw data consists of four data tables. As an operational database, the data is not necessarily in a format that lends itself to analysis. Each data table is designed to serve a function within GCSS-MC day-to-day operations. GCSS-MC is largely a commercial-off-the-shelf database so the data tables contain many fields that are not commonly used today. A list of each table and its fields is provided in Appendix A: *Data Tables and Fields*. A description and the general purpose of each table follows.

SR_HEADER table. This table provides information about the service request and is oriented toward maintenance functions. In GCSS-MC the service request is the primary worksheet used to track tasks performed in pursuit of a maintenance or supply function. Service request header information includes the unit, identifying characteristics of the equipment in maintenance, descriptions of the fault, and the operational status of the equipment. This table includes a dead-lined control date used in part to calculate DDL. This table consisted of 42 fields and 235,018 service request instances.

GCSS2_SR_REPAIR_PART_HST table. This table is intended to provide a transaction cost summary. It contains a partial historical record of transactions by service request that accounts for the cost of parts and an estimated cost of labor. The cost data in this table contains a large amount of null values indicating that utilization of this table has not been fully implemented. Service Request Number, RNSN, and Document Number are present in this table and can be considered candidate keys depending on the information requirement. This table consists of 23 fields and 552,355 service request instances. Due to the inconsistent quality of the data on this table, its use is largely excluded from this analysis.

GCSS2_DUE_IN_STAT table. This table tracks the status of orders and provides date stamped status updates for actions taken on each order. This information is used daily by a requesting unit's Due in Status File (DASF) clerk to verify that the correct parts are on-order and are shipping within an acceptable timeframe. The DASF clerk can then intercede when order delays are anticipated and report potential problems up the chain of command. This table contains the two-letter Defense Logistics Agency

(DLA) status code that identifies document numbers with backorders. It also provides the backorder quantity. This table consists of 29 fields and 1,099,821 status update instances.

GCSS2_HST_DUE_IN table. This table includes fields required to place orders and capture historical demand data. Based on current inventory policy, this table is a useful reference to established inventory levels. It contains required NSNs, source information, quantities ordered, ship and received dates, priority information, and item price information. It does not contain information on inventory position such as on-hand quantity or re-order point. This is the primary table referenced and adapted for analysis purposes. This table consists of 49 fields and 247,967 document number instances.

2. Important Data Fields

The data tables, as provided, retain no relationships, that link the tables or keys that identify unique records. The fields of service request number, document number, and NSN are common throughout the tables. These fields are used as keys to reconstruct the relationships between the tables allowing for fields on different tables associated with a single, unique document number. A description of each of these fields follows.

Document Number. This field appears in three of the four tables as “DOCUMENT_NUMBER” and is used as a primary unit of measure throughout the analysis. Each document number is a unique fourteen digit, alpha-numeric code that represents an order of a varying quantity of a single NSN. The first six digits provide the requesting units AAC. Each service request can contain multiple document numbers. For this analysis, document number is used to link the tables on which it appears, and as a primary key on GCSS2_HST_DUE_IN table.

Service Request Number. This field also appears on three of the data tables and is abbreviated as “SR_NUMBER.” Each maintenance fault is assigned a service request number to allow for the tracking of tasks performed by maintenance and supply functions and to relate these tasks back to a specific piece of equipment. Service request number is a unique, non-repeated value on the GCSS2_SR_REPAIR_PART_HST and SR_HEADER tables. Service request number is used to link the tables on which it appears and as the primary key for the two tables on which it was a unique value.

National Stock Number (NSN). The NSN is the number used to uniquely identify a specific part. This field appears in the data set as “RNSN” on two tables and as “NSN” on a third. In this study, NSN is used for sorting parts during fill-rate calculations.

Since NSN contains coding that identifies the supplier, there are instances where an item may have more than one valid NSN that has changed over time as different sourcing contracts were awarded. The data set does not provide sufficient information to account for this anomaly, nor is there sufficient information to estimate the frequency of occurrence or its impact on the analysis. For the purposes of this study, NSN is assumed to identify a unique and distinct item.

3. Derived Fields and Dummy Variables

The data set does not directly provide certain variables that are required for this analysis. The following factors are transformations of the information available in the data set.

Customer Wait Time. Approximate customer wait time is calculated from the GCSS2_HST_DUE_IN table. The DATE_ESTABLISHED field provides the date an order was placed and the ORDER_CLOSED_DATE field provides the approximate date the order was received. Because the Marine Corps does not employ automated tools to clock order or received times, this approximation includes data entry time for the supply clerk to place the order and potential data entry delays in recording the receipt of parts. Administrative delay is unobserved, but it is potentially an influential driver of variability in the data set. Certain data cleaning assumptions used in this study are specifically aimed at reducing the influence of this factor in the analysis.

Monthly Fill Rate per NSN. This study considers fill-rate per NSN, aggregated monthly. The quantity ordered per document number is provided in the ORDERED_QTY field of the GCSS2_HST_DUE_IN table. The field BACK_ORDER_QTY is present in two of the four tables, but contains no values. Document numbers with backorders are identified using the STATUS_CODE field of the GCSS2_DUE_IN_STAT table which contains DLA status codes. In the dataset, the “BB” code and “BM” code indicate backorders. The QUANTITY field for instances with either of these two codes provides

the value for quantity of backordered NSNs associated with each document number. Monthly fill rate is calculated using the following function:

$$\text{Monthly Fill-rate} = \frac{(\text{Quantity Ordered per Month} - \text{Quantity Backordered per Month})}{\text{Quantity Ordered per Month}}$$

This formula is an effective method for fill-rate calculation assuming that one month is a sufficient amount of time to capture a single order cycle.

Days Dead-lined (DDL) by Service Request. Marine Corps equipment readiness information reported in Defense Readiness Reporting System (DRRS) is not directly accessible due to classification; however, the metric of DDL is captured automatically by GCSS-MC for all dead-lining service requests. DDL is the number of days an end item is not able to perform its primary mission due to a maintenance fault. In this study, DDL is used to estimate operational availability.

LOGCOM provided a list of 1391 service request numbers from the original data set and their associated number of days dead-lined. The list includes all service requests with a DDL one or greater. Service requests not included in this list are assumed to have a DDL of less than one day or did not possess a dead-lining fault. The DEADLINE_DATE in the SR_HEADER table represents the start date from which to calculate DDL. Service requests with a dead-line date, but a DDL of less than one are assumed to have been repaired within 24 hours. These service requests are added to the LOGCOM list and included in the analysis with a DDL value of zero.

SECREP identification. This research is only concerned with consumable repair parts. The data provided includes all repair part orders including those for SECREPS. SECREPS had to be identified and filtered out of the data used for analysis.

GCSS-MC discerns between SECREPS and consumables using an attribute labeled “Item Type” and another called “SECREP flag” which refer to a list of all current SECREP NSN’s. Based on cost and demand criteria, at different times, some repair parts

can move between designation as a SECREP or a consumable. The “Item Type” and “SECREP flag” values reflect only the current designation of the part, so using either field to reconstruct historical usage patterns results in an error that excludes parts that changed status over time (J. T. Milazzo, personal communication, June 27, 2016). This research uses Acquisition Activity Codes (AAC) as an alternate method for identifying SECREPS.

LOGCOM authorizes certain organizations to issue SECREPS. With the authorization, the issuing organization is provided an additional AAC under which they conduct all SECREP transactions. The organization uses different AAC for consumables transactions. A unit’s AAC is captured in several fields within GCSS-MC and LOGCOM provided a complete listing of 106 authorized SECREP issuing AACs.

B. ANALYSIS METHODS

This study uses linear regression techniques to test the statistical relationship between CWT, Fill-rate, and DDL. Once the presence of a relationship is established, we will explore the practical implications of the fill-rate-only measurement system by categorizing the data quadrants based on thresholds for acceptable and unacceptable outcomes. The quadrant model illustrates situations that when using fill-rate exclusively may adversely impact supply chain performance.

1. Linear Regression Analysis

The first goal of this study is to establish the relationship between CWT, Fill-rate and DDL as an indicator of impact on operational availability (A_O). DDL over time provides a time scalable metric that can be used to demonstrate the operational impact of the selected performance measures in terms of materiel availability over time.

Based on DDL, the definition for A_O is stated as:

$$A_O = \frac{\text{Uptime}}{\text{Total time}} = 1 - \frac{\text{DDL}}{\text{Total Time}}$$

This approximation for A_O is drawn from the Pryor's simple function for operational availability and does not include other variables considered in his more complex aggregate function of A_O (Pryor 2008). Notably, this method does not account for the non-operational time required for other essential maintenance not associated with a dead-lining failure. As such the use of DDL is adequate to represent A_O in this analysis, but it should not be considered an adequate replacement for A_O for all applications.

DDL is the dependent variable for the linear regression model. The methods used to approximate the independent variables of CWT and fill-rate were discussed in the previous section. The proposed regression model is:

$$y_{DDL} = \beta_0 + \beta_1 (CWT) + \beta_2 (\text{fill-rate}) + \beta_3 (CWT) \times (\text{fill-rate}) + u$$

Based on the intuitive relationship between the variables, the expected sign for β_1 should be positive indicating that if CWT increases (or decreases), DDL will move in the same direction. Conversely, the expected sign for β_2 should be negative indicating that a high fill-rate will experience lower DDL values and visa-versa.

The third term in the equation is an interaction variable that accounts for the influence that CWT and fill-rate have on each other. By including this term and holding it constant, the calculation of the incremental effect of each of the other two variables is possible. The “ u ” term contains all other unknown or unobservable factors not considered in this model.

Given the wide range and differing distributions of the data, each variable is centered by subtracting the mean value for the variable in the data set from the value for the particular data point. This demeaning sets the expected intercept (β_0) value to zero and reduces the effect of skewed data distribution on the interaction variable.

2. Categorization and the Comparison Framework

Next, we categorize the values for CWT and fill-rate into quadrants based on acceptable and unacceptable outcomes for each measure. The purpose of this

categorization is to further explore the interaction of CWT and fill-rate in the context of current policy that emphasizes fill-rate as the exclusive metric of supply chain performance. Figure 2 illustrates the quadrant model and provides some characteristics and effects of the orders that fall into each category.

The initial thresholds used in the categorization are 90% for fill-rate, and three days for CWT. Based on observation and current performance levels in each of these measures, the thresholds are intentionally set very high to represent nearly ideal performance. The threshold values are adjusted for sensitivity analysis and to demonstrate how differing policy decisions and expectations can affect the supply chain outcomes.

		Customer Wait Time	
		Short	Long
Fill Rate	High	<u>Quadrant One: Acceptable Outcome</u> <ul style="list-style-type: none"> - No problem exists - Stock-outs are rare and corrected quickly due to short CWT. - Inventory levels can be kept relatively low. - Fill rate appears to function adequately as a measure of customer satisfaction. 	<u>Quadrant Two: False Positive</u> <ul style="list-style-type: none"> - Potential problem exists: stock-outs are rare, but when they occur fill rate does not capture the extended CWT back orders. - No problem is detected or reported based on high fill rate. - Stock out situations have significant negative impacts on equipment readiness. - Inventory levels have to be kept very high to accommodate the long lead time for replenishment.
	Low	<u>Quadrant Three: False Negative</u> <ul style="list-style-type: none"> - No problem exists: short CWT satisfies customer's requirement despite stock-outs. - Negligible impact on equipment readiness. - Problem is perceived based on low fill rate. - To increase fill rate, unnecessary inventory is purchased. 	<u>Quadrant Four: Unacceptable Outcome</u> <ul style="list-style-type: none"> - Problem exists: stock-outs are frequent and CWT is long for backorders - Problem is detected in terms of fill rate. - Stock out situations have significant negative impacts on equipment readiness. - To increase fill rate, purchasing large quantities of inventory is incentivized.

Figure 2. Characteristics of Fill-Rate versus Customer Wait Time.

Quadrant one represents an acceptable supply chain outcome as measured by both factors of CWT and fill-rate. The high fill-rate reports that there are no supply chain problems apparent. CWT is relatively short, theoretically allowing for smaller inventories to maintain acceptable fill-rate levels. In this analysis, quadrant one may also contain

some items that should be categorized in other quadrants, but did not experience a back-order and as such did not provide a data point for analysis.

In quadrant two, items experience high fill-rates but unacceptably long CWTs when a backorder occurs. The current system does not recognize a problem, because CWT is not actively monitored. To maintain a high-fill rate, relatively large inventories must be kept on hand to offset the long order time required for replenishment. If an item eventually goes out of stock, a relatively large inventory purchase is required to replenish inventory and reset fill-rate levels. This action does not necessarily address the underlying problem, rather it satisfies the fill-rate metric with inventory. This quadrant provides a false positive measure of supply chain performance because the fill-rate indicates acceptable outcome while the long CWT contributes to both delivery delays and larger, more expensive inventory levels.

In quadrant three, the system recognizes a problem when a fill rate is low, even if the item possesses an acceptably short CWT. This results in maintaining a stock of items that are not necessarily required to satisfy customer expectations. This quadrant provides a false negative measure of supply chain performance because fill-rate indicates a problem, even when expedited delivery times provide an acceptable supply chain outcome.

Quadrant four represents a failure of the supply chain. This quadrant contains items that have both an unacceptably low fill-rate, and an unacceptably long CWT. Items that fall into this category are recognized as problems. Inventory purchases that replenish and maintain sufficient safety stocks can elevate items from quadrant four to quadrant two, the false negative. This again results in larger on hand inventories and their associated expense. Because CWT is not monitored, decreasing CWT is not considered as an option for improving performance in this quadrant.

By relying solely on fill-rate, the Marine Corps supply system is misallocating resources to address problems that do not adversely impact performance. It is also possible that excess inventory levels are being maintained to compensate for long CWT when addressing CWT directly could be more cost effective.

C. ASSUMPTIONS AND LIMITATIONS IN THE DATA

1. Assumptions in the Data

The methods previously discussed rely on certain assumptions to focus the analysis and simplify calculations. In addition, the data set contains numerous missing values and entries that represent illogical values. Assumptions are also used to clean the data and replace missing values before regression analysis. These assumptions are as follows:

1. One month is sufficient time to capture an entire order cycle that allows for the use of the fill-rate formula in this analysis.
2. Items with negative fill-rates represent orders with quantities intentionally increased beyond immediate demand to refill stock on hand. Negative fill-rates are considered zero for the purposes of analysis.
3. Orders with no backorder quantity are assumed to have been filled from stock. The value of zero replaced missing back-order quantities that results in a 100% immediate fill-rate.
4. The DLA status code indicators of “BB” and “BM” are sufficient to identify back-ordered parts in this analysis.
5. Service requests with no dead-line control date (DCD) are considered to possess non-dead-lining faults and have not impact on A_0 . These service requests and their associated document numbers are excluded from the analysis.
6. Service requests with a DCD, but do not appear on “DDL list” provided by LOGCOM are assumed to have been dead-lined for less than one day. The value of zero is used in the place of missing values for DDL.
7. Order quantities of zero and over 10,000 are assumed to be erroneous entries and are removed from the data set.
8. For NSN’s with 100% fill-rate, CWT should be near zero. For these parts, all CWT values greater than 5 days are assumed to be attributable to administrative delays and are excluded from the analysis.
9. During initial analysis, Urgency of Need Designator (UND) code is found to be statistically insignificant for predicting DDL indicating that UND code did not sufficiently identify the dead-lining part on order. Therefore, in order to reduce the effect of parts in the data set that did not contribute to the dead-lining fault, records with a DDL value of zero and a CWT of five days or greater are removed. This serves the dual purpose of removing non-dead-lining parts as well as late entries due to administrative delays in receipting for parts.

Assumptions 1–4 pertain to fill-rate calculations and assumptions 5–7 refine DDL values. Assumptions 8 and 9 limit CWT to reduce the influence of unreasonably long administrative processing times. Assumption 9 also removes repair parts ordered for non-dead-lining faults.

2. Limitations of the Data

1. The data does not have any indicators for non-traditional sourcing methods such as the use of open purchase options. Relying on the DLA status code in assumption 4, to identify backorders may understate the number of backorders in situations where non-traditional sourcing options were utilized. Assumption 8 may reduce, but does not eliminate this source of variation in the data.
2. In assumption 6, by replacing missing DDL values with zero when equipment assumed to be dead-lined for less than one day, the influence of DDL is slightly understated. Using a positive, fractional values will compensate for this, but fractional DDL values are not available in the data.
3. This model is unable to break CWT into its component parts including order lead time to the SMU and delivery time from the SMU to the customer. These component factors will provide added granularity to the analysis that is not possible with the data provided.

D. CHARACTERISTICS OF DATA USED IN ANALYSIS

The cleaned and coded data set consists of 12,340 records. Figure 3 provides a histogram for each of the variables as well as some summary statistics.

Each variable exhibits a high proportion of zero values that affect the shape of the distribution. For DDL and CWT the resulting distribution appears exponential in shape. Removing the zero values results in a more linear distribution for DDL and a more Poisson-like distribution for CWT. Further investigation of the actual distribution of each of these variables is warranted, but outside the scope of this study. The exponential distribution is accepted for analysis purposes.

Fill-rate exhibits a nearly binary distribution. This is due to approximately 95% of orders being placed for a single part. As a result, instantaneous order fill-rate has a high proportion of zero and one values. Since demand for consumable repair parts is highly

intermittent, this trend toward binary values is also apparent in the aggregated monthly fill-rate. The binary nature of the fill-rate data affects the interpretation of the linear regression model.

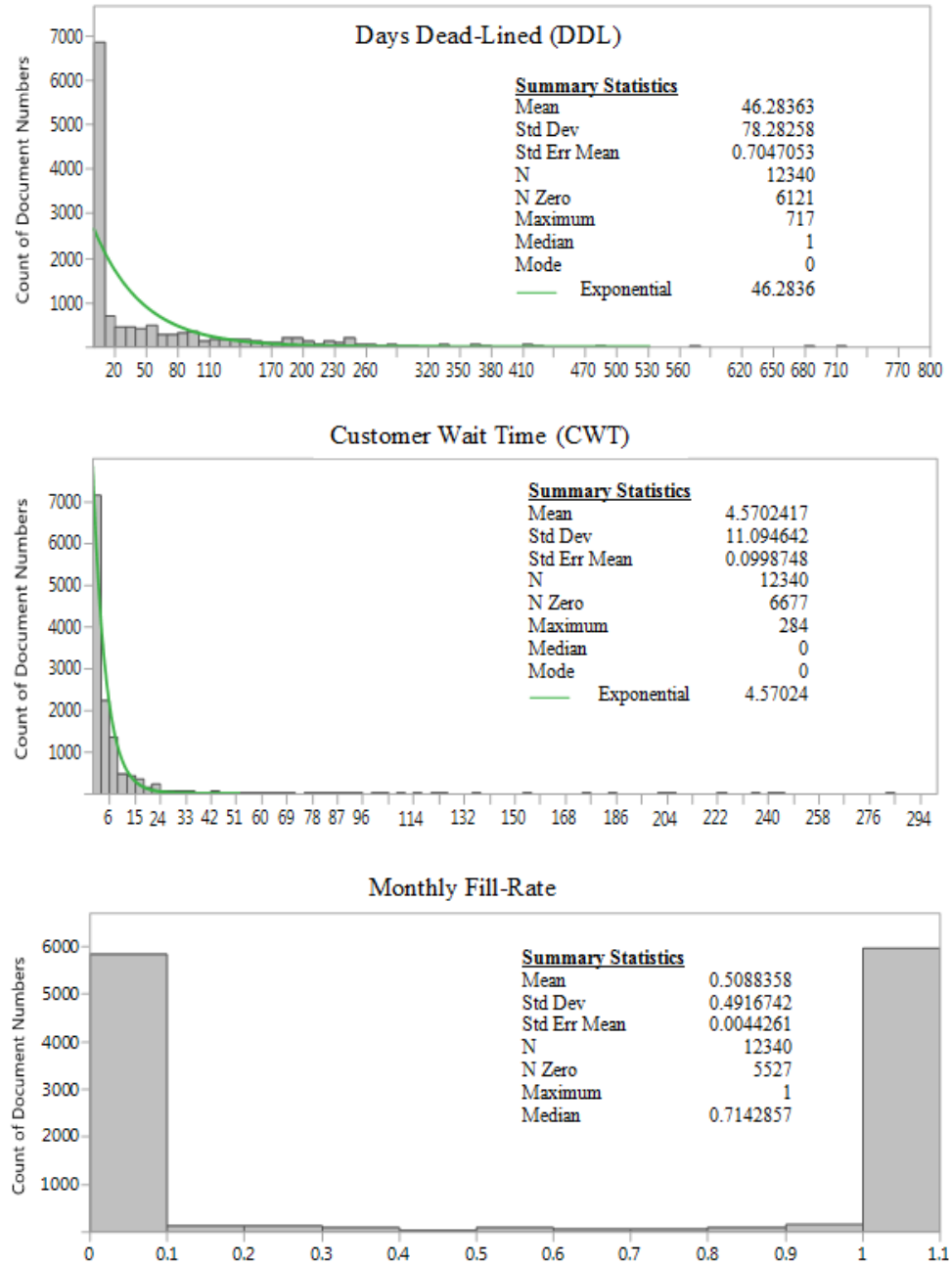


Figure 3. Distribution and Summary Statistics of Variables

Given the apparent distribution of each variable, it is important to note that using the mean as the measure of centrality could be misleading as the means of DDL and CWT are heavily influenced by extreme tail values. Since monthly fill-rate values other than 0 or 1 are relatively rare, the mean fill-rate is of limited use. Conversely, relying on the median or mode as a measure of centrality provides an overly optimistic view of performance as measured by each metric.

This chapter describes the methods used to clean and code the data, the proposed methods of analysis including assumptions and limitations, and provided the characteristics of the resulting data set. The next section will provide the results of the analysis.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. ANALYSIS AND RESULTS

This chapter answers each research question using the methodology discussed in Chapter III. First, a linear regression model describes the influence of fill-rate and CWT on DDL. Next, a categorization model describes the magnitude of the practical effect of relying on fill-rate as a single metric for supply chain performance. Based on the experience of working through the data in pursuit of these models, the third section assesses the quality of the GCSS-MC data for making timely and accurate supply chain management decisions. Finally, the effects of each independent variable is discussed briefly.

A. LINEAR REGRESSION RESULTS

This section addresses research question number one: **To what extent does CWT and fill-rate for consumable repair parts affect the equipment readiness of Marine Corps mechanized systems?**

Linear regression on the data refined from GCSS-MC produces a model for the relationship between the demeaned dependent variable of DDL and the demeaned independent variables of CWT and fill-rate, as well as a demeaned interaction variable. Table 1 provides the linear regression summary output from JMP® Pro 12. This linear regression model considers 12,340 observations. This relatively large quantity contributes to low p-values for each variable. Each of the variables is highly significant to the 0.01 level indicating that they are relevant predictors of DDL in this model. The high statistical significance of the two independent variables suggests that the expected relationship exists between the variables; however, the presence of a statistically significant interaction variable complicates the interpretation of the influence of each independent variable. The statistical significance of the interaction variable is sufficient evidence to conclude that fill-rate should not be considered in isolation without considering the effects of CWT.

Table 1. Linear Regression Summary

Summary							
RSquare		0.12					
RSquare Adj		0.12					
Root Mean Square Error		73.57					
Mean of Response		-1.7e-12					
Observations (or Sum Wgts)		12340					
Source of Variance	DF	Sum of Squares	Mean Square	F Ratio			
Model	3	8841493	2947164	544.47			
Error	12336	66773902	5413	Prob > F			
C. Total	12339	75615395		<.0001			
Term		Estimate	Std Error	t Ratio	Prob> t 	Lower 95%	Upper 95%
Intercept		1.16	0.75	1.53	0.13	-0.32	2.63
CWT		0.59	0.09	6.71	<.0001	0.42	0.77
Monthly Fill-rate		-48.91	1.52	-32.21	<.0001	-51.88	-45.93
CWT * Monthly Fill-rate		0.60	0.19	3.20	0.001	0.23	0.96

As expected, due to the centering of all terms, the returned intercept value is not statistically different than zero. The coefficient of CWT is positive indicating that CWT and DDL are positively correlated (i.e., a shorter CWT is associated with a shorter DDL and vice versa). The p-value of less than 0.0001 indicates that this is a highly statically significant relationship. Also as expected, the coefficient of fill-rate is negative indicating that fill-rate and DDL are negatively correlated and move in opposite directions. The p-value of less than 0.0001 indicates that this is also a highly statically significant relationship. Fill-rate is measured in percentage so the coefficient value must be divided by 100 to indicate the influence of a single percent change. These coefficients should not be interpreted further without considering the influence of the interaction variable.

The interaction variable is included to account for potential correlation between fill-rate and CWT so that it can be held constant for analysis. The interaction variable's p-value of 0.001 indicates that there is a highly statistically significant interaction between CWT and fill-rate that affects DDL. This significant interaction between CWT

and fill-rate is the most important finding provided by the linear regression analysis. Each measure of performance is a predictor of DDL in this model, but each is influenced by the other so neither measure can be used in isolation as a single measure of supply chain effectiveness measured in DDL. Figure 4 provides the JMP® Pro 12 Interaction Profiles for CWT and fill-rate as they apply to DDL

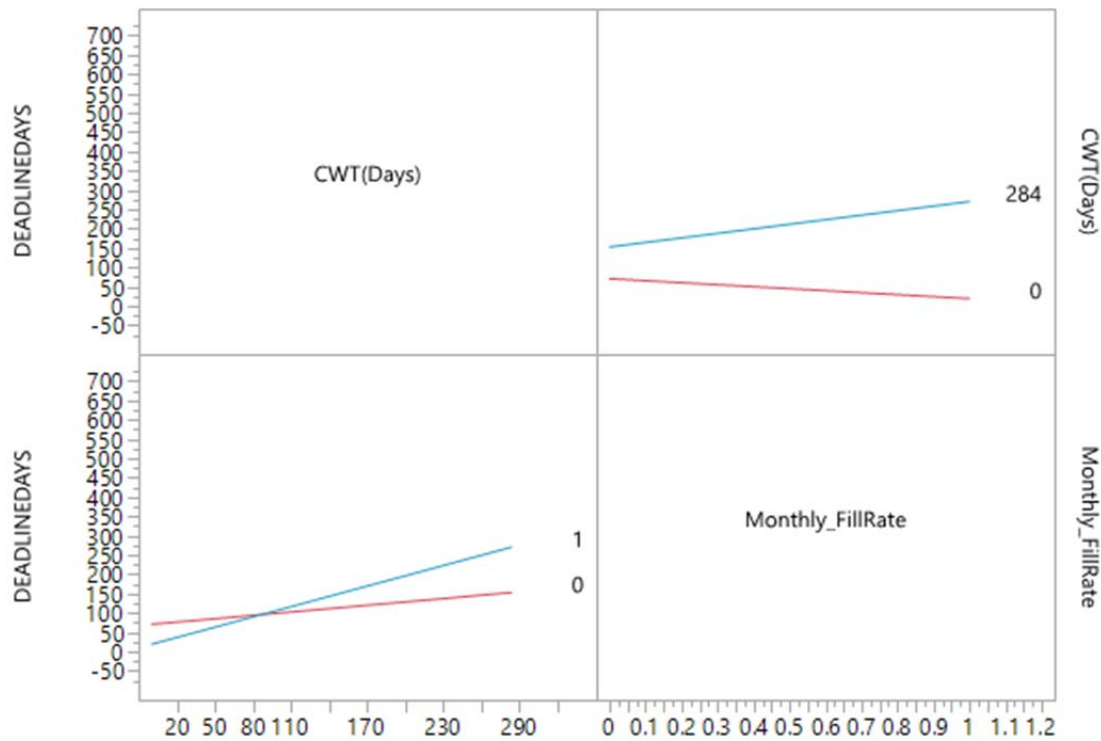


Figure 4. Interaction Profiles

To simplify interpretation, actual variable values are depicted versus the demeaned values used for the regression model. This has no effect on the slope or practical interpretation of the graphs, except that the intercept shifts to a value greater than zero. Actual variable values are used for the remainder of this analysis.

The coefficient of the interaction variable is positive, which indicates that in general the influence of CWT on DDL increases as fill-rate increases between zero and one; however, the interaction plots depicted in Figure 4 make it clear that the relationship is not linear or monotonic.

In the upper right quadrant of Figure 4, the red line indicates the results of the regression model when CWT is at its minimum value of zero. The blue line is the maximum CWT of 284 days. The space between the diverging lines illustrates the impact on DDL of increasing fill-rate from 0 to 1. When CWT is short, the relationship is negative: increasing fill-rate decreases DDL. The opposite is true when CWT is long. In this case, the relationship between fill-rate and DDL is positive: increasing fill-rate results in increased DDL. This suggests a convex relationship between fill-rate and CWT on DDL.

In the lower left quadrant, the red line illustrates the result of the regression model when fill-rate is zero; the blue line is the result when fill-rate is 1. The converging lines indicate that the interaction between CWT and fill-rate is disordinal, further implying that though the main effects are significant, they should not be interpreted in isolation.

As CWT increases between 0 and approximately 82 days, the effect of fill-rate on DDL behaves as expected. Fill-rates near 1 result in lower DDL than fill-rates near 0. The predicted DDL values at these extreme fill-rate levels converge at approximately 82 days, after which, the higher fill-rate values actually result in longer DDLs. When CWT is low, performance measured in DDL is shorter with fill-rates near 1. When CWT is longer than 82 days, DDL performance is shorter with fill-rates near 0. This also indicates a convex relationship between fill-rate and CWT on DDL.

The evidence presented in this subsection provides strong support for the proposition that fill-rate may not be a sufficient metric for reporting supply chain outcomes. The next section will discuss some of the practical implications of this result.

B. RESULTS OF DATA CATEGORIZATION

This section addresses research question number two: **Does reliance on fill-rate as the exclusive indicator of supply chain performance have a negative impact on supply-chain performance?**

For this discussion, we assume that from the perspective of a maintenance customer a part with a short CWT is acceptable regardless of whether that part is issued

from the SMU inventory, or provided from another source of supply. Table 2 contains the results of categorizing the data based on the initial thresholds (i.e., performance targets) of 90% or greater for monthly fill-rate, and three days or less for CWT.

Table 2. Categorization Results.

Fill-rate \geq 90% CWT < 3 days	Quadrant 1: Acceptable Outcome	Quadrant 2: False Positive	Quadrant 3: False Negative	Quadrant 4: Unacceptable Outcome
Orders in category	5582	485	1744	4529
Percent of orders	45.24%	3.93%	14.13%	36.70%
Mean CWT	0.12	5.02	0.54	11.5
Mean fill-rate	99.91%	99.80%	7.68%	1.85%

True Acceptable Outcome (Q1+Q3)	59.37%
True Unacceptable Outcome (Q2+Q4)	40.63%
Accurately Reported (Q1+Q4)	81.94%
Misreported (Q2+Q3)	18.06%

Quadrant one includes all parts with a fill-rate of 90% or better and a CWT of three days or less. This quadrant captures situations where the use of fill-rate as a performance metric aligns with the maintenance customer's time-driven requirements. It also includes situations where the fill-rate is not perfect, but the supply chain is responsive enough to provide the ordered part within three days. Approximately 45% of orders observed fall into this quadrant. The CWT is 0.12 days indicating that orders in this quadrant experience high supply chain responsiveness on average.

Quadrant two includes those parts that have a fill-rate above 90%, but experience CWTs longer than three days. 3.93% of parts fall into this category. This low proportion is explained by the dynamic nature of this quadrant. When a part falls into this category, if the SMU takes action to replenish inventory, then the part quickly shifts into quadrant one. If no action is taken, the part just as quickly shifts to quadrant four. The mean CWT in quadrant two is 5.02 days, so this quadrant does not appear to have serious negative consequences using these tight tolerances for threshold values—customers are waiting

just a few days longer than desirable on average. The primary implication of this quadrant is that fill-rate reports a positive situation when parts in this category should be recognized as potential problems. There are also a small percentage of parts (less than 1% of total orders) with very long CWTs in the extreme tail values of this quadrant that should be recognized as serious problems, but are not registered on the basis of fill-rate alone.

Quadrant three contains parts with a CWT of less than three days, and a fill-rate lower than 90%. The mean CWT is 0.54 days, so this quadrant is also very responsive. On the basis of fill-rate, these parts may be reported as problems, but the short CWT provides an acceptable outcome for the maintenance customer in most cases. 14.13% of orders fall into this category. Similarly to quadrant two, if action is taken to replenish inventory, orders with these characteristics can be shifted into quadrant one. This is the second situation where fill-rate could be misreporting actual performance. Any actions taken to address these misreported problems is unnecessarily work that results in a misallocation of resources and time.

Quadrant four represents an unacceptable supply chain outcome. Parts in this quadrant have fill-rates lower than 90% and CWTs longer than three days. These orders are recognized as problems using fill-rate alone; however, the extent of the problem in terms of time is not apparent. In this quadrant, the maintenance customer is not satisfied because the part is out of stock, and because it takes a longer than ideal amount of time to receive the part from another source. 36.70% of orders fall into this category based on the initial threshold values. The mean CWT is 11.5 days. This CWT value does not necessarily imply a serious problem, but the mean value may not be the best indicator in this case. The distribution of CWT in this category is exponential, so the mean CWT is influenced positively by a large proportion of the parts near the three-day threshold. Aspects of this quadrant are very sensitive to shifting the threshold values that we discuss further in the next section.

Additional insights are apparent by combining quadrant proportional values. Quadrants one and three provide the number of orders that meet the CWT threshold and provide a true acceptable outcome from the perspective of the maintenance customer.

Quadrants two and four provide the number of orders that do not meet the CWT threshold and represent a true unacceptable outcome. Quadrants one and four provide the proportion of orders that are accurately reported as acceptable or unacceptable on the basis of a 90% fill-rate and by coincidence experience the same outcome on the basis of CWT. Quadrants two and three contain those orders that are not accurately reported using the fill-rate measure versus the CWT standard.

Overall, using the 90% or greater fill-rate and three day or less CWT thresholds indicates that the Marine Corps supply system experiences true acceptable outcomes approximately 59% of the time. Relying on fill-rate as the single metric for supply chain performance results in a misreporting of performance 18% of the time. Next we will adjust each threshold value and discuss the implications of the new results.

1. Sensitivity Analysis of the Categorization Model

To examine effect of differing fill-rate threshold values, we hold the CWT threshold constant at three days or less and the fill-rate threshold is adjusted in increments of 10%. At the three-day CWT threshold, the proportion of parts in each category is relatively unresponsive to reductions in the fill-rate threshold until the fill-rate approaches zero. The results are summarized in Figure 5.

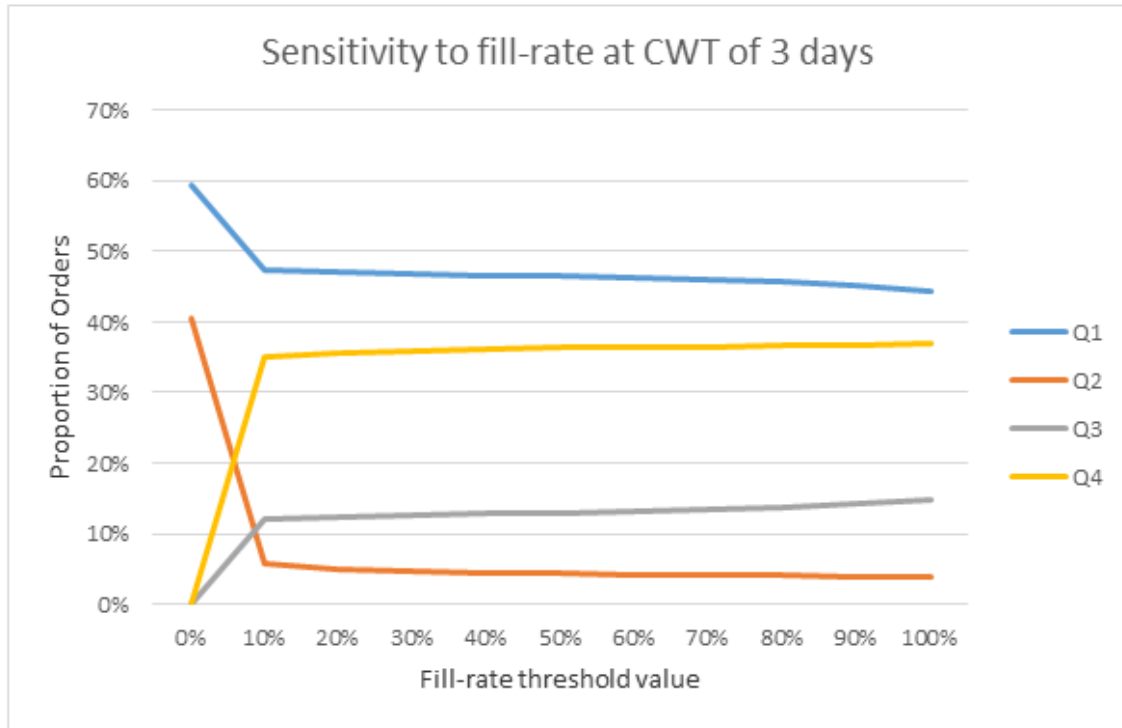


Figure 5. Sensitivity to Fill-Rate

The increments of this graph are insufficient to show that the fill-rate is unresponsive to at least the 0.001% fill-rate level. This is to the binary nature of monthly fill-rate in the data. Parts with a 100% fill-rate are provided within three-days approximately 45% of the time. This proportion does not change significantly until the fill-rate threshold reaches zero, at which point the model becomes highly sensitive.

Closer examination of the median value of 50% fill-rate reveals additional insights as summarized in Table 3.

Table 3. Categorization Results with Fill-Rate of 50%

Fill-rate \geq 50% CWT < 3 days	Quadrant 1: Acceptable Outcome	Quadrant 2: False Positive	Quadrant 3: False Negative	Quadrant 4: Unacceptable Outcome
Orders in category	5745	538	1581	4476
Percent of orders	46.56%	4.36%	12.81%	36.27%
Mean CWT	0.12	7.53	0.59	77.73
Mean fill-rate	99.04%	96.65%	1.32%	1.07%

True Acceptable Outcome (Q1+Q3)	59.37%
True Unacceptable Outcome (Q2+Q4)	40.63%
Accurately Reported (Q1+Q4)	82.83%
Misreported (Q2+Q3)	17.17%

True acceptable outcomes as measured by CWT (quadrants one and three) still occur approximately 59% of the time because the proportion of orders received in three days or less is constant regardless of fill-rate level. The most notable change is in the mean CWT for quadrant four, which increases from 11.5 days to 77.73 days. This implies that as the acceptable performance level for fill-rate is relaxed, by the time the system registers a problem, the magnitude of the problem is much larger in terms of time.

2. Sensitivity to the CWT threshold

For the next sensitivity analysis, we return the fill-rate threshold to its original value of 90% and we adjust the CWT threshold value incrementally from one to fourteen days. Fourteen days as an extreme value is selected based on the Marine Corps Uniform Material Movement and Issue Priority (UMMIP) order (USMC, 2010) that establishes a fourteen-day time-definite-delivery standard for repair parts inside CONUS. This value is considered a maximum value for a positive outcome from the supply community's perspective. Results are summarized in Figure 6.

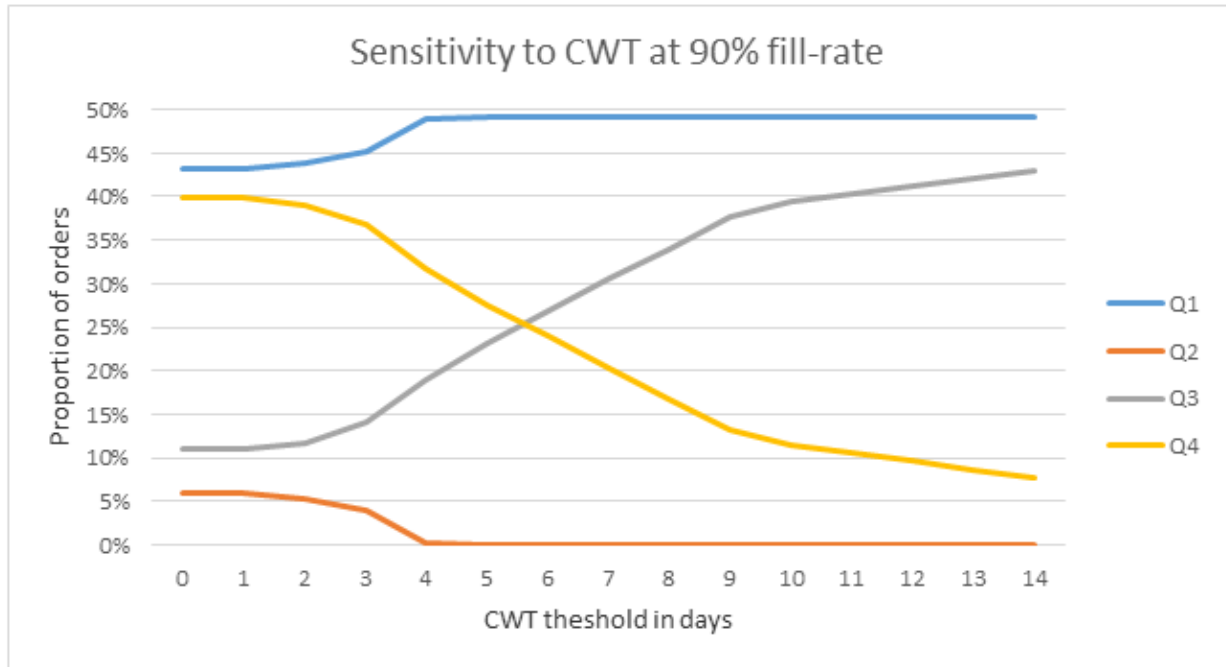


Figure 6. Sensitivity Analysis to CWT

The categorization model is highly sensitive to adjustments in the CWT threshold, particularly at smaller values. Quadrants one and two are responsive to shifts in the CWT threshold out to four days at which point they reach their maximum and minimum values respectively. Quadrants three and four converge and cross between five and six days. As the acceptable CWT threshold is relaxed, fewer orders fall into the unacceptable outcome quadrant four. This is not to say that the situation is improving, rather that we are relaxing what we consider to be a problem.

Due to the model's high sensitivity to the CWT threshold, the aggregate effects on reporting accuracy is also highly sensitive. The performance of reporting in fill-rate versus the performance reported in CWT is displayed in Figure 7.

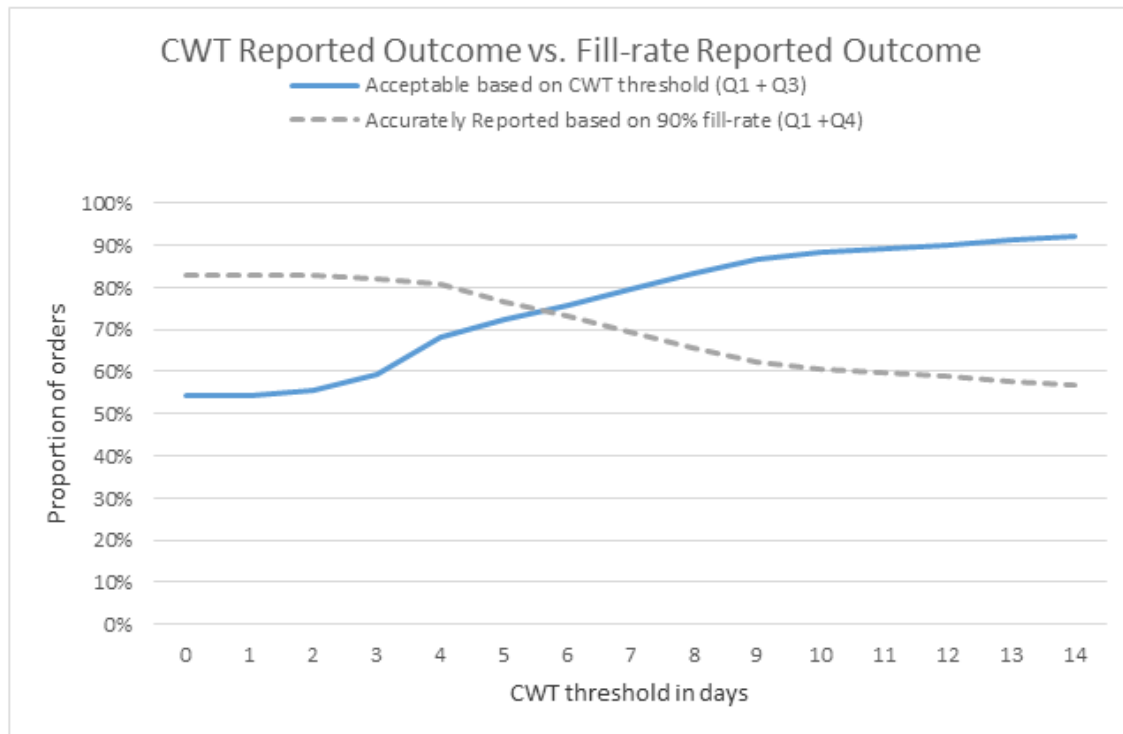


Figure 7. CWT versus Fill-Rate Reported Outcomes

As the acceptable CWT threshold increases, the proportion of orders that experience an acceptable outcome increase as a result of the relaxing standard. This does not imply an increase in performance from the customer's perspective, only a lessor standard from supply's perspective. For short target CWTs, performance from the maintenance customer's perspective is a significant concern that is not identified by fill-rate based reporting that returns relatively high marks for short CWT orders.

The accuracy of reporting via fill-rate decreases as the CWT threshold is relaxed and the quadrant four proportion of unacceptable outcomes shrinks. At the UMMIP standard value of fourteen days CWT, fill-rate based reporting is only accurate approximately 56% of the time though over 92% of orders meet that CWT standard. The categorization model further provides strong evidence that fill-rate is not sufficient as a single measure of supply chain performance.

The reporting percent-in-quadrant response surfaces cross between five and six days, which could imply a logical threshold value for CWT. Since each surface is

composed of completely separate orders this crossing point is misleading. Any orders that are properly reported by both fill-rate and CWT at this point, are reported accurately only by coincidence. The inflection points in the response surfaces are more telling and could be used for establishing logical threshold values. This will be discussed further in the recommendations section of Chapter V.

C. GCSS-MC DATA QUALITY

This section addresses research question number three: **Are current data collection practices that use GCSS-MC sufficient to provide Marine Corps supply-chain managers the information they need for accurate and timely decision making?** This secondary research question is less quantifiable than the two primary questions and results are the opinion of the author based on experience and observations taken while working with the GCSS-MC data during this study.

GCSS-MC is a robust and adaptable system that is capable of capturing and reporting sufficient information for management purposes, but the GCSS-MC data provided may not currently provide sufficient information for supply-chain managers to make timely and accurate decisions for two reasons: 1) Primary measures of performance are not calculated automatically by the system, and 2) Data collection methods are not capturing all components of DDL and as a result there is too much unexplained variation in the data.

Fill-rate and DDL are both current performance measures based on Marine Corps policies and/or practices. CWT is a DOD directed performance measure, though it has not been fully implemented. None of these performance measures are available as independent data fields, calculated and provided automatically by GCSS-MC. Marine Corps supply managers at the intermediate and organizational levels do not typically have the time and expertise to perform the data transformations required to distill this information from the data available in GCSS-MC. Without these metrics as separate, automatically generated data fields, the timeliness of decisions based on these measures is adversely affected. Also, due to the possibility of differing data collection and

transformation techniques data integrity is questionable if the system is not automatically providing the standard measures.

Models for operational availability have many factors that include but are not limited to the time required to perform the repair, and administrative processing time. (Pryor, 2008). Without including these additional factors in the data collection strategy, resulting predictive models for DDL are not complete. By omitting influential predictors of DDL from the data collection process, potential problem areas are not apparent and the effectiveness of supply chain decisions could be adversely impacted by these unobservable factors.

D. EFFECT ANALYSIS

While statistically significant, the linear regression model only provides an R^2 of 0.117 indicating CWT, fill-rate, and their interaction only account for 11.7% of the variation in DDL. This limitation is discussed further in Chapter V, but is mentioned here to introduce the topic of the relative effects of each variable. Though only a small proportion of the variation is accounted for using the linear regression model, the factor of fill-rate in particular demonstrates a noticeable effect on DDL.

Table 4 provides the three common measures of effects for each independent variable calculated using JMP® Pro 12. The values provided for Eta squared, Partial Eta squared, and Omega squared all indicate similar relative values for the effect of each source on the outcome of DDL. According to Cohen's (1988) scales of magnitude for effect sizes, CWT and the interaction variable both exhibit a very small effect on DDL whereas fill-rate shows a medium sized effect on DDL. Given that DDL has many known factors, the discovery of a single factor with at least a medium effect worthy of note.

Table 4. Effects Report

Source	<i>df</i>	Sum of Squares	F Ratio	Prob > F	Eta Squared	Partial Eta Squared	Omega Squared
CWT	1	243914	45.06	<.0001	0.0032	0.0036	0.0032
Monthly Fill-rate	1	5616930.7	1037.69	<.0001	0.074	0.078	0.074
CWT * Monthly Fill-rate	1	55509.9	10.26	0.0014	0.00073	0.00083	0.00066

Though fill-rate is not sufficient to indicate supply chain performance alone, it should be considered an important and influential predictor of DDL and included in the list of measures required to manage the supply chain for repair parts. The effect of CWT seems minor, but as previously discussed, fill-rate and CWT are inseparable based on their interaction's influence on DDL. Further exploration of the effect size of differing factors contributing to DDL is worthy of further research, but is outside the scope of this analysis. The next chapter will summarize these results and provide recommendations for improvement based on these findings, as well as recommend areas for further research.

V. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

This research explores the effect of CWT and fill-rate on equipment operational availability using GCSS-MC data to determine if the current system's reliance on fill-rate as the primary indicator of supply chain performance adversely affects the operational availability of equipment. This study provides the background and history of the two measures within DOD and industry. It then analyzes approximately three years of supply and maintenance data for consumable repair part orders originating with the Marine Corps' mechanized units of Tanks, AAVs, and LAVs. It uses linear regression techniques and a categorization model developed specifically for this analysis to draw the conclusions provided in this chapter. This study also captures specific observations on the quality and scope of GCSS-MC data.

A. EFFECTS OF CWT AND FILL RATE ON EQUIPMENT READINESS

To what extent does CWT and fill-rate for consumable repair parts affect the equipment readiness of Marine Corps mechanized systems?

1. Summary and Conclusions

Linear regression on data refined from GCSS-MC produces the following model for the relationship between the dependent variable of DDL and the independent variables of CWT and fill-rate.

$$Y_{DDL} = \underset{(0.754)}{1.156} + \underset{(0.088)}{0.592} (CWT) - \underset{(1.518)}{48.906} (\text{fill-rate}) + \underset{(0.186)}{0.596} (CWT) \times (\text{fill-rate}) + u$$

$$N = 12,340, R^2 = 0.117$$

For the regression model, all variables are centered via demeaning and an interaction variable is included to account for correlation between the main independent variables. Each variable returned p-values less than 0.001 indicating high statistical significance. The model suggests that the intuitive relationship exists between the main variables; however, the presence of a statistically significant interaction variable

complicates the interpretation of the influence of the main effects. The statistical significance and characteristics of the interaction variable is sufficient evidence to conclude that fill-rate should not be considered in isolation without considering the effects of CWT.

2. Recommendations

Balance inventory performance with supply chain responsiveness. Both fill-rate and CWT are significant predictors of DDL, but neither fill-rate nor CWT is an adequate predictor of DDL alone. For this reason, Marine Corps supply-chain performance should be managed using both measures concurrently with the goal of balancing inventory performance with supply chain responsiveness.

Fill-rate is a useful measure of inventory performance at the individual supply node that indicates if the supply node is accurately forecasting and stocking the correct parts to meet demand. It is also a useful indicator of customer satisfaction as measured in the proportion of orders filled from stock on the first pass.

CWT is a different measure of customer satisfaction that considers the time required to receive an order regardless of whether the order is filled from SMU stock or from another source. CWT spans supply nodes, providing an arguably better indication of supply-chain performance versus the supply-node performance indicated by fill-rate. CWT cannot, however, provide inventory performance information and a 100% fill-rate does not guarantee an acceptable CWT. The two measures are inter-related to an extent that each must be considered in the context of the other.

To balance inventory performance with supply-chain responsiveness, minimal inventory levels should be maintained for parts with acceptable CWT from the non-SMU sources of supply. Inventory forecasting and management should focus on parts with CWTs that do not satisfy the maintenance customer and 100% fill-rates should be the target for parts with longer CWTs.

This analysis did not address cost concerns specifically, but when deciding which parts are stocked and which are not, the trade-off in terms of cost in addition to

performance must also be considered. Total inventory holding costs need to be compared with the cost of expediting delivery from an external source. Industry research indicates that emphasizing speed of delivery in favor of holding inventory typically reduces supply costs (Gunasekaran., Patel, & Tirtiroglu, 2001).

B. FILL-RATE AS THE SINGLE SUPPLY CHAIN METRIC

Does reliance on fill-rate as the exclusive indicator of supply chain performance have negative impact on supply-chain performance?

1. Summary and Conclusions

Reliance on fill-rate as the single measure of supply chain performance for consumable repair parts results in misreporting of supply chain effectiveness 20–40% of the time depending on the CWT threshold considered acceptable from the perspective of the maintenance customer. As the CWT standard increases, the accuracy of fill-rate as an indicator of supply chain performance decreases. When performance is reported in terms of fill-rate, the UMMIPS guidance of a fourteen-day CWT standard within CONUS results in misreporting supply-chain performance for 40% of orders.

2. Recommendations

Improve inventory performance for long CWT parts. Fill-rate is unsuitable as a single indicator of supply chain performance; however, it is still a valid and influential predictor of DDL. Simple moving average forecasting techniques may be inadequate for forecasting the intermittent demand demonstrated in repair parts. Improving inventory management to include using more accurate forecasting techniques and exploring demand consolidation options would have significant positive effects on equipment operational availability.

As measured on a monthly basis, fill-rate exhibits largely binary distribution with mostly zero or 100% values. Therefore, target fill-rates should be 100% for parts that are not available within established CWT standards. Since most orders are for a single repair part, the SMU should maintain a wider range of parts on hand with low stock levels for each, instead of high stock levels for some and zero inventory for others. This is contrary

to the concept of dollar-cost-banding proposed by the RAND Corporation (Fricker & Robbins, 2000), which advocates carrying larger stocks of inexpensive critical parts to maximize fill-rate.

Aggregating demand signals to a level higher than the regional SMU and enabling expedited shipment would allow for reduced safety stock at all SMU locations due to the properties of overlapping demand variation. If demand is low and intermittent for a particular part, the Marine Corps should keep a minimal stock level of that part on hand somewhere in the supply system. When the part is required, as long as the supply system is responsive enough to get the part to the requestor within an acceptable timeframe, then the physical location of the inventory has little impact on the supply system outcome. Funneling requests through the local SMU slows overall supply-chain responsiveness and increases the inventory requirements at each independent SMU.

Establish logical CWT standards and goals based on historical data. There is an apparent inflection point in the CWT response curve at approximately ten days, that indicates that there is very little additional effort required to attain a ten-day CWT versus the current fourteen-day standard set by UMMIPS. Ten days is therefore a logical maximum CWT standard for consumable repair parts based on the data provided. There is another inflection point at approximately three days where the CWT response curve begins to flatten. This indicates that there is a diminishing rate of return on efforts to pursue CWT shorter than three days. This implies that a three-day or less CWT is a logical target goal for Marine Corps supply chain responsiveness within the scope of equipment sets considered in this research. This study only considered data from Tanks, AAVs, and LAVs, so data from other equipment types may or may not indicate similar threshold values.

C. GCSS-MC DATA QUALITY

Are current data collection practices that use GCSS-MC sufficient to provide Marine Corps supply-chain managers the information they need for accurate and timely decision making?

1. Summary and Conclusions

GCSS-MC is capable of capturing and reporting sufficient information for management purposes, but GCSS-MC data does not currently provide sufficient information for supply-chain managers to make timely and accurate decisions for two reasons: 1) Primary measures of performance are not automatically calculated and provided by the system, and 2) Data collection methods are not capturing all components of DDL and as a result there is too much unexplainable variation in the data.

2. Recommendations

Target the data collection strategy on the drivers of DDL. If DDL is considered an adequate measure of supply chain effectiveness for repair parts, then GCSS-MC needs to be oriented to capture and directly report more of DDL's determining factors including but not limited to order lead-time to the SMU, maintenance time/time to repair, and other administrative or logistics delay time (Pryor, 2008). Some of these fields are currently unobservable components of CWT and others are not currently collected or calculated by GCSS-MC at all. Expansion of the data collection strategy to specifically capture the known contributors to DDL would allow for more accurate and relevant analysis. Conversely, eliminating data collection fields that are not utilized in Marine Corps supply and maintenance operations would serve to reduce the size of the database in general and could potentially provide increased processing speed in certain applications.

Automate data collection, analysis, and reporting. As a service, the Marine Corps has taken the giant step of investing in ERP technology, but it has not fielded any of the commercially available toolkits that enable the technology to perform analysis nor has it enabled dashboard functionality to perform statistical control functions. The Oracle system is performing basic transactions required for the operation of the supply system and is collecting large amounts of data. Unfortunately, without the analysis toolkits the data cannot be utilized to control or improve supply chain operations without significant investment of time and expertise. Microsoft Office applications currently used by the

Marine Corps to observe the data are not sufficient to perform continuous monitoring or analysis of the data.

The Marine Corps is relying on physical data entry to capture important data such as time of receipt. This process is error prone and subject to delay. Significant quantities of illogical values are present in the raw data indicating that there is an interminable amount of error in the data collection processes. GCSS-MC is capturing data exactly as it is entered into the system, so errors and delays are recorded as entered. GCSS-MC is a robust and adaptable system that could accommodate a higher level of automation in data collection processes. The Marine Corps would benefit from a thorough process improvement project targeted at eliminating or automating steps in the data collection process. For any time-stamped data, gating technology and/or bar code scanners should be employed to reduce administrative delay and error in receipting for orders. By improving the data collection process, supply and maintenance operational processes would become more transparent. This is a necessary first step for achieving supply-chain efficiency.

D. LIMITATIONS OF THE MODEL

- Predicting DDL is beyond the capabilities of this model. Since the linear model only considers two independent variables it is not intended to be used as a complete predictive model for DDL. The returned R^2 of 0.117 indicates that only 11.7% percent of the variation in the DDL is explained by CWT, fill-rate, and their interaction. The low R^2 is acceptable for the purpose of the analysis conducted in this study.
- The practical effect of the binary nature of the distribution of fill-rate means that this relationship is most accurate at the extreme values of 0% and 100%. Fill-rate values that fall in between the extremes may not predict DDL with any accuracy using a linear model.
- Repair parts that did not experience a back-order during the timeframe of this analysis possess unobservable CWTs. As a result, the influence of CWT may be understated.
- Since the current Marine Corps supply system primarily utilizes (and incentivizes) fill-rate as an indicator of supply chain performance, it is possible that regression results will overstate the actual influence of fill-rate due to institutional bias.

- Since this study focuses on equipment that the Marine Corps considers high priority, there may be an institutional bias toward maintaining high operational availability. Fill-rates may be higher, and DDL may be lower for this equipment population than that for non-priority equipment.

E. RECOMMENDATIONS FOR FURTHER RESEARCH

The linear regression model used in this analysis is limited to two independent variables and resulted in a relatively small predictive value for DDL. Determining the other factors that affect DDL and building a more complete predictive regression model would be very useful for further Marine Corps supply chain improvement efforts.

Analysis of the historical data indicates that, similar to industry, demand for Marine Corps consumable repair parts is highly intermittent. Current Marine Corp inventory forecasting techniques are not sophisticated enough to accurately forecast for intermittent demand. Further research to determine the most accurate intermittent forecasting model is required to improve Marine Corps consumable repair part inventory performance. Technological enablers should be capitalized on to pursue more complex, automated forecasting techniques such as variations of the Croston method (Shenstone & Hyndman, 2005) to better match forecasts with actual demand. There are commercially available programs designed to integrate with Oracle systems that could provide supply-chain managers with the tools required for their task. The Marine Corps should explore and invest in these options.

With the investment in GCSS-MC, the Marine Corps has opened the door to conduct data-driven, supply-chain process improvement. Any further research that explores this broad area of study is of value and serves to justify the acquisition of the system.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX. DATA TABLES AND FIELDS

GCSS2_HST_DUE_IN
SOURCE
ORDER_NUMBER
SHIP_FROM_ORG
SHIP_TO_ORG
DOCUMENT_NUMBER
DOC_ID_CODE
RNSN
ORDERED_QTY
SHIP_RECIEVED_QTY
CANCELLED_QTY
BACK_ORDER_QTY
UNIT_OF_ISSUE
DESTINATION_SUBINVENTORY
PURPOSE_CODE
LAST_STATEMENT_DATE
NEXT_FOLLOW_UP
RIC
APPROVED_DATE
ADVICE_CODE
CONDITION_CODE
DEMAND_CODE
DISTRIBUTION_CODE
PRIORITY_CODE
PROJECT_CODE
REQUIRED_DELIVERY_DATE
SIGNAL_CODE
SUPPLEMENTAL_ADDRESS
JOB_ORDER_NUMBER
SR_NUMBER
TASK_NUMBER
LAST_UPDATE_DATE
FILE_ID
LEGACY_FILE_DTTM
ORACLE_REPLACE_DTTM
TRANSACTION_TYPE
DATE_ESTABLISHED
MAT_TRANS_ID_NUM
ORDER_CLOSED_DATE
SHIPPED_QTY
STATUS_QTY
UNIT_PRICE
LAST_KNOWN HOLDER
MEDIA_STATUS_CODE
ORDER_LINE_STATUS
RAC
REF_DOCUMENT_NUMBER
REQUIREMENT_NUMBER
SUFFIX_CODE
HST_DOCNUM_RANK

247,967 instances

SR_HEADER
SERVICE_REQUEST_TYPE
SR_NUMBER
JOB_STATUS_CODE
DEFECT_CODE
OPERATIONAL_STATUS
PROBLEM_SUMMARY
DATE_RECIEVED_IN_SHOP
ECHOLON_OF_MAINT
NSN_IN_MAINTENANCE
SERIAL_NUMBER
QUANTITY_INDUCTED
UNIT_ISSUE_CODE
TAMCN
DEADLINED_DATE
MAINT_CATEGORY_CODE
MASTER_PRIORITY_CODE
HOLD_UNIT_IDENT_CODE
ONWER_UNIT_ADDRESS_CODE
UNIT_NAME
ITEM_DESIGNATOR_NUMBER
JOB_STATUS_DATE
SR_XREF
SR_OPENED_BY
DATE_CLOSED
OPENED_DATE
EQUIP_OP_TIME_CODE
METER_READING
MILITARY_LABOR_HOURS
TOT_CIV_LAB_EXPENSE
TOTAL_EQUIP_OPER_TIME
TASK_NAME
LAST_UPDATE
FILE_ID
LEGACY_FILE_DTTM
ORACLE_REPLC_DTTM
RECORD_LAST_CHANGE_DATE
CUSTOMER_NAME
MIMMS_RAC
RESOURCE_NAME_OWNER
SR_CUSTOMER
SR HOLDER
SR_RANK

235,018 instances

GCSS2_DUE_IN_STAT
TBL_SOURCE
DOCUMENT_NUMBER
DOC_IDENT_CODE
QUANTITY
DUE_QTY
BACK_ORDER_QTY
RECEIVED_QTY
STATUS_CODE
MODE_OF_SHIPMENT
DATE_SHIPPED
RIC_PASS_TO
LAST_KNOWN HOLDER
SUFFIX_CODE
STATUS_DATE
TRAN_CNTRL_NUM_NSN
LAST_UPDATE_DATE
FILE_ID
LEGACY_FILE_DTTM
ORACLE_REPLC_DTTM
SOURCE
RIC
ORDER_TYPE
ORDER_NUMBER
NSN
DISCREP_IND_CODE
CONDITION_CODE
MAT_TRANS_ID_NUM
ESTIMATED_SHIP_DATE
STAT_RANK

1,099,821 instances

GCSS2_SR_REPAIR_PART_HST
SR_NUMBER
TASK-NUMBER
SERVICE_ACTIVITY
ORGANIZATION_CODE
RNSN
QUANTITY_REQUIRED
DEMAND_CODE
SIGNAL_CODE
PARTS_CHARGE
DOCUMENT_NUMBER
STATUS_DATE
DATE_RECIEVED_CANCELLED
SUPP_STATUS_DIC
LAST_UPDATE_DATE
FILE_ID
LEGACY_FILE_ID
ORACLE_REPLC_DTTM
TRANS_LAST_UPDATE
MAT_TRANS_ID_NUM
REQUIREMENT_NUM
SERIAL_NUMBER
REPLACEMENT_SDN
SALES_ORDER_NUMBER

552,355 instances

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

- Berg, J. (May 2013). *LRC and Intermediate Supply Reach-Back*. Brief presented at the Installation and Logistics Board, 1st Marine Logistics Group, Camp Pendleton, CA. Retrieved from http://www.iandl.marines.mil/Portals/85/Docs/Division%20LP%20Documents/6_Log%20Board_1st%20MLG.ppt
- Christopher, M. (2000). The agile supply chain: Competing in volatile markets. *Industrial Marketing Management*, 29(1), 37–44. Retrieved from <http://www.sciencedirect.com/science/article/pii/S0019850199001108>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.
- Coleman, B. J. (2000). Determining the correct service level target. *Production and Inventory Management Journal*, 41(1), 19–23.
- Defense Contract Management Agency. (2002). *Performance based logistics (PBL) support guidebook*. Retrieved from: <https://acc.dau.mil/adl/en-US/54825/file/18745/PBL-GUIDE.doc>
- Department of Defense. (2000). *Customer wait time and time definite delivery* (DODI 4140.61). Washington, DC: Office of the Under Secretary of Defense for Acquisitions, Technology, and Logistics. Retrieved from: <http://www.dtic.mil/whs/directives/corres/pdf/414061p.pdf>
- Department of Defense. (2014). *DOD supply chain materiel management reporting procedures: Metrics and inventory stratification reporting*. (Department of Defense Manual 4140.01, Volume 10). Washington, DC: Office of the Under Secretary of Defense for Acquisitions, Technology, and Logistics. Retrieved from: http://www.dtic.mil/whs/directives/corres/pdf/414001m/414001m_vol0.pdf
- Dumond, J., Brauner, M. K., Eden, R., Folkesson, J., Girardini, K., Keyser, D., Wang, M. Y. D. (2001). *Velocity management the business paradigm that has transformed U.S. army logistics* (MR-1108). Santa Monica, CA: RAND Corporation. Retrieved from http://www.rand.org/pubs/monograph_reports/MR1108.html.
- Fricker Jr., R. D., & Robbins, M. (2000). *Retooling for the logistics revolution: Designing marine corps inventories to support the warfighter* (MR-1096-USMC). Santa Monica, CA: RAND Corporation. Retrieved from http://www.rand.org/pubs/monograph_reports/MR1096.html

- Gunasekaran, A., Patel, E. Tirtiroglu, (2001) Performance measures and metrics in a supply chain environment. *International Journal of Operations & Production Management*, 21(1/2), 71–87. Retrieved from <http://dx.doi.org/10.1108/01443570110358468>
- Hines, P., Howle, M., & Rich, N. (2004). Learning to evolve a review of contemporary lean thinking. *International Journal of Operations and Production Management*, 9/10, 994–1011. Retrieved from <http://search.proquest.com.libproxy.nps.edu/business/docview/232364114/fulltextPDF/7775CE9CAFEF425FPQ/1?accountid=12702>
- Inspector General (IG). (2007). *Uniform standards for customer wait time* (D-2007–111). United States Department of Defense. Retrieved from: <http://www.dodig.mil/Audit/reports/FY07/07-111.pdf>
- Jones D.T., Hines, P. & Rich, N. (1997). Lean logistics. *International Journal of Physical Distribution & Logistics Management*, 27(3/4), 153–173. Retrieved from <http://dx.doi.org/10.1108/09600039710170557>
- Lee, H.L. & Billington, C. (1992) Managing supply chain inventory: Pitfalls and opportunities. *Sloan Management Review*, 33(3), 65–73. Retrieved at <http://search.proquest.com.libproxy.nps.edu/business/docview/224958815/E3C5424E0A8E4963PQ/1?accountid=12702>
- Martin, P. R., Patterson, J.W. (2009). On measuring company within a supply chain. *International Journal of Production Research*, 47(9), 2449–2460. Retrieved from <http://dx.doi.org/10.1080/00207540701725604>
- Nahmias, S. (2009). *Production and operations analysis*. (6th ed., 272–274) New York. McGraw-Hill Companies, Inc.
- Piotrowicz P. & Cuthbertson R. (2015). Performance measurement and metrics in supply chains: an exploratory study. *International Journal of Productivity and Performance Management*, 64 (8), 1068–1091. Retrieved from <http://dx.doi.org/10.1108/IJPPM-04-2014-0064>
- Pryor, G.A. (2008). Methodology for estimation of operational availability as applied to military systems. *ITEA Journal*, 29, 420–428. Retrieved from <http://dtic.mil/cgi-bin/GetTRDoc?AD=ADA518378>
- Shenstone, L. & Hyndman, R. (2005). Stochastic models underlying Croston's method for intermittent demand forecasting. Retrieved from <http://www.robjhyndman.com/papers/croston.pdf>
- Stalk, G. (1988, July). Time—The next source of competitive advantage. *Harvard Business Review*. Retrieved from <https://hbr.org/1988/07/time-the-next-source-of-competitive-advantage#>

- Stalk, G. & Hood, T. (1990). *Competing against time*. New York: The Free Press.
- Syntetos, A. A. & Boylan, J.E. (2006). On the stock control performance of intermittent demand estimators. *International Journal of Production Economics*, 103, 36–47. Retrieved from http://ac.els-cdn.com/S0925527305001507/1-s2.0-S0925527305001507-main.pdf?_tid=e7050d88-33f3-11e6-912b-00000aacb35f&acdnat=1466103512_436c1be14b3238a08023b84acc1d40de
- Thorn, D. & Hubbard M. (2012). *Investigating the relationship between customer wait time and operational availability through simulation modeling* (MBA project). Retrieved from Calhoun <http://hdl.handle.net/10945/27914>
- United States Government Accountability Office. (2015). *Defense logistics improvements needed to accurately assess the performance of DOD's materiel distribution pipeline* (GAO-15-226): Washington, DC: Author. Retrieved from GAO website: <http://www.gao.gov/assets/670/668732.pdf>
- United States Marine Corps. (2010). *Uniform material movement and issue priority system* (MCO 4400.16H). Washington, DC: Author. Retrieved from Marines website: <http://www.marines.mil/Portals/59/Publications/MCO%204400.16H.pdf>
- United States Marine Corps (2012a). *Intermediate-level supply management policy manual* (MCO P4400.151b Ch2). Washington, DC: Retrieved from <http://www.marines.mil/Portals/59/MCO%20P4400.151B%20W%20CH%201-2.pdf>
- United States Marine Corps (2012b). Ground equipment conditions and supply materiel readiness reporting (MRR) policy (MCO 3000.11E). Washington, DC: Retrieved from <http://www.marines.mil/Portals/59/MCO%203000.11E.pdf>
- United States Marine Corps (2012c). *Marine Corps coordinated secondary reparable management (CSM) program* (MCO 4400.200). Washington, DC: Author. Retrieved from <http://www.marines.mil/Portals/59/MCO%204400.200.pdf>
- United States Marine Corps (2012d). *Marine Corps Integrated Maintenance Management System (MIMMS) Field Manual* (MCO 4790.2C). Washington, DC: Retrieved from Marines website: <http://www.marines.mil/Portals/59/MCO%20P4790.2C%20W%20CH%201-2.pdf>
- United States Marine Corps (2014). *Consumer-level supply policy* (MCO 4400.150). Washington, DC: Author. Retrieved from Marines website: <http://www.marines.mil/Portals/59/Publications/MCO%204400.150.pdf>
- Willemain, T.R., Smart, C.N. & Schwarz, H.F. (2004). A new approach to forecasting intermittent demand for service parts inventories. *International Journal of Forecasting*, 20, 375–387. Retrieved from <http://torpedo.nrl.navy.mil.libproxy.nps.edu/tu/ps/doc.html?dsn=3610477>

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
Ft. Belvoir, Virginia
2. Dudley Knox Library
Naval Postgraduate School
Monterey, California